Le rôle des comportements paysans dans leur insécurité alimentaire

Mémoire pour l'habilitation à diriger des recherches

T. Le Cotty *

4 mai 2021

*CIRAD-CIRED, Montpellier, France, lecotty@cirad.fr

Table des matières

Remerciements

Je tiens à remercier Emmanuelle Bouquet d'avoir accepté d'être référente pour ce mémoire et pour sa relecture très utile, ses conseils, sa bienveillance et sa caution scientifique. Je remercie aussi très sincèrement mes co-auteurs qui ont beaucoup apporté à ce travail, principalement Elodie Maître d'Hôtel qui a contribué à toutes mes recherches, mais aussi Raphaël Soubeyran, Julie Subervie, Antoine Leblois, Yves Gérard Bazié, Audrier Sanou, Damien Oula Ouattara, Moctar Ndiaye et Henri Leturque. J'ai connu avec eux des échecs, des désaccords de temps en temps, mais surtout beaucoup de bonheur et le sentiment d'une grande aventure. Je remercie avec la même gratitude Issoufou Porgo, mon partenaire de terrain, pour la patience et la confiance avec lesquelles il m'a accompagné tant de fois dans des villages du Burkina Faso, du matin au soir, pendant des semaines. On a vécu ensemble tant de rencontres, et c'est à ses côtés que j'ai appris à interagir avec les paysans du burkina et à commencer à les comprendre un peu. Je remercie Issoufou Yaka pour les enquêtes que nous avons menées ensemble et tous les enquêteurs que j'ai cotoyés. Merci aussi Zono, notre chauffeur, avec qui j'ai noué une proximité particulière presque sans se parler, pendant 6 ans, en écoutant pendant des heures ses vieilles cassettes disco sur les pistes poussiéreuses du Burkina. Merci à chaque paysan qui m'a consacré du temps et a bien voulu m'instruire. Les rencontres avec beaucoup d'entre eux ont été pour moi des moments bouleversants et pleins d'enseignement.

Je remercie le Cirad de m'avoir soutenu pendant toute mon expatriation, Pierre Montagne en premier lieu, Serge Marlet, Jacqueline Badolo, Sylvain Perret, François Laporte, Michel Eddi. Je remerice aussi le Cired ne m'avoir permis cette expatriation, et notamment Franck Lecocq pour sa constance et son exigeance sereine. Merci enfin à mes parents, mes soeurs, Elodie, et tous les amis qui m'ont soutenu dans les moments difficiles.

" Poser le plat pour qu'il refroidisse
c'est attendre celui qui va le manger",
proverbe mossi

Résumé

Mes recherches visent à étudier les comportements des paysans du Sahel qui expliquent leur insécurité alimentaire saisonnière. Dans les principaux courants de pensée de l'économie du développement, les paysans en insécurité alimentaire en Afrique subissent les contraintes agro-climatiques, institutionnelles ou économiques (les défaillances de marché en particulier), et ne sont pas acteurs de leur insécurité alimentaire. Ce n'est que récemment, grâce aux apports de l'économie comportementale, que les économistes du développement s'intéressent aux comportements "paradoxaux", ou "difficiles à expliquer par la recherche de l'optimum", qui pourraient jouer un rôle dans l'insécurité alimentaire. Mon travail entre 2012 et 2020 a consisté à analyser l'existence de choix qui interpellent, à les expliquer, et à mettre en évidence leurs conséquences sur l'insécurité alimentaire saisonnière. Ces choix portent sur les arbitrages intertemporels qui se traduisent par un faible investissement dans la production pour certains ménages, une vitesse d'épuisement des stocks céréaliers plus rapide que souhaitée pour certains ménages, des ventes paradoxales de céréales qui entretiennent une volatilité locale atypique des prix. Bien que premièrement identifiés comme "paradoxaux", ces comportements sont le plus souvent cohérents avec la volonté de se soustraire à la pression sociale. Ces comportements sont d'abord identifiés empiriquement (de manière expérimentale ou économétrique) et puis représentés dans mon travail par des modèles théoriques. Ce mémoire expose les résultats de 6 articles publiés depuis 2017, 2 articles en cours et un projet en phase initiale. Concernant mes travaux passés, 3 sont des confirmations d'une origine comportementale de l'insécurité alimentaire ((i) la préférence pour le présent réduit l'investissement des paysans, (ii) le biais pour le présent rend l'épuisement des stocks plus rapide qu'à l'optimum défini par le ménage lui-même, (iii) les erreurs d'anticipation créent une volatilité locale des prix), et 3 sont des implications indirectes de ces résultats ((i) l'investissement peut être accru par un crédit en soudure, (ii) l'impact du warrantage sur la sécurité alimentaire est quantitativement significatif, (iii) la volatilité atypique est plus grande dans les villages retirés). Mes travaux en cours sur les politiques de lutte contre l'insécurité alimentaire et le changement climatique confirment la faible efficacité des politiques publiques contre l'insécurité alimentaire ((i) la demande d'assurance sécheresses diminue lorsque les sécheresses sont plus fréquentes, (ii) les aides alimentaires au Niger sont plutôt bénéfiques à court terme et problématiques à long terme), et mon projet de recherche à développer vise à mesurer la pression sociale et son impact sur les investissements dans un contexte de changement climatique. Les politiques publiques seraient plus efficaces si elles prenaient en compte les aspects comportementaux des ménages vulnérables qui cherchent à échapper à la pression sociale.

Keywords : sécurité alimentaire, Afrique Sub Saharienne, Sahel, Burkina Faso, Niger, Soudure, Préférences Temporelles, Volatilité, Stocks

JEL codes : D12, D13, Q12

1 Introduction

Le plus souvent, l'insécurité alimentaire des paysans est analysée comme une résultante de facteurs extérieurs aux populations agricoles : le climat, le sol, les institutions, les défaillances de marché, les conséquences de l'histoire, l'indisponibilité technologique. Les choix des ménages ne sont généralement pas en cause dans leur insécurité alimentaire. Les explications comportementales de l'insécurité alimentaire sont rares, et peut-être difficiles à aborder sereinement en France en raison de l'héritage colonial. Dans cette tradition de l'économie du développement post coloniale, il est malvenu de s'interroger sur la part de responsabilité des mal nourris dans leur malnutrition. Dans quelle mesure l'insécurité alimentaire saisonnière des paysans sahéliens est-elle la résultante de leurs choix ? Mes travaux envisagent la possibilité de poser cette question et d'y apporter des éléments aussi empiriques que possible, en mettant en évidence certains déterminants comportementaux de l'insécurité alimentaire des paysans au Sahel.

Plusieurs comportements réguliers conduisent les ménages à se mettre en insécurité alimentaire. En particulier, de nombreux ménages semblent épuiser leurs stocks de céréales plus rapidement qu'ils ne le feraient s'ils avaient le projet d'éviter l'insécurité alimentaire de soudure avant la prochaine récolte. Pour expliquer ce déstockage précoce, l'absence de crédit est la principale raison avancée Burke et al. (2018). Mais l'absence de crédit n'explique pas tous les aspects du déstockage précoce, comme par exemple les nombreuses cérémonies après la récolte, associées à des dépenses inconsidérées " (Maranz, 2001) ou "extravagantes" (Foster, 1965). De plus en plus d'aspects du déstockage précoce sont interprêtés comme des stratégies pour se soustraire à la pression sociale. Pour Maranz (2001), les dépenses de cérémonies d'après récoltes seraient des stratégies pour réduire la pression des proches qui font des demandes "d'emprunt". Foster (1965) écrit : "une personne qui améliore sa situation est encouragée à restaurer l'équilibre initial à travers une consommation visible sous la forme de rituels extravagants" qui est "un mécanisme de redistribution qui permet à une personne ou une famille qui risquerait de menacer la stabilité de la communauté de restaurer graciseusement le status quo." Les sanctions villageoises contre celui qui ne redistribue pas les bénéfices de son travail associent souvent les menaces d'ordre surnaturel et les sanctions matérielles (le "wak"). Platteau (2000); Comola and Fafchamps (2010) mettent en évidence l'importance des dons unilatéraux résultant d'obligations sociales et familiales unilatérales, plutôt que du lien de réciprocité plus abondamment décrit dans la litérature (Coate and Ravallion, 1993). Dans le même esprit, Baland et al. (2011) interprètent certains comportements atypiques comme des comportements de pauvreté simulée. Jakiela and Ozier (2016); Goldberg (2017); Di Falco and Bulte (2011) montrent que les paysans préfèrent gagner moins, mais de manière plus dissimulée, pour échapper à la pression sociale. Contrairement à un postulat fréquent dans le monde du développement, tous les producteurs n'ont pas forcément pour but d'épargner et d'investir, parce que le contexte social n'est pas toujours favorable aux producteurs qui épargnent et investissent. Les fruits de l'épargne et de l'investissement ne sont pas facilement conservés par ceux qui investissent.

L'économie comportementale propose une vision des choix individuels reposant sur une dimension psychologique plus explicite de l'homme, avec des tensions internes dans les choix des

individus, ou des erreurs de jugement de leur part. Les travaux les plus déterminants dans ce sens ont été ceux de Slovic et al. (1977); Kunreuther and Slovic (1978); Kahneman and Tversky (1979) concernant les choix face au risque, et Loewenstein and Prelec (1992); Laibson (1997); O'Donoghue and Rabin (1999); Harris and Laibson (2001); Prelec (2004); Laibson (2015) concernant les choix intertemporels. Les applications les plus importantes à l'économie du développement sont probablement (Ashraf et al., 2006; Duflo et al., 2011a). L'économie comportementale que je mobilise s'intéresse aux désaccords inter-temporels internes de l'homme (le moi d'aujourd'hui sous-estime la préférence pour le présent du moi de demain, et le moi de demain ne respecte pas le plan qu'avait prévu le moi d'aujourd'hui). Ces désaccords permettent d'expliquer le recours à des mécanismes auto-contraignants, ce que la simple impatience ne peut expliquer, ni la stratégie rationnelle. Mes méthodes combinent la modélisation théorique, le RCT, l'économie expérimentale (lab in the field), et l'économétrie de survey.

L'utilisation détaillée de la littérature et mes contributions sont présentées ci-dessous article par article. Le mémoire comporte 4 sections [1], les sections 3, 4 et 5 portent sur mes travaux passés, et la section 6 porte sur mes travaux en cours et futurs. Chaque sous-section correspond à un article. Sur les 8 articles présentés, 6 sont publiés et 2 sont en cours. Les sections 3, 4 et 5 visent à interpréter des comportements paradoxaux ou susceptibles de conduire à l'insécurité alimetaire des ménages qui adoptent ces comportements : pourquoi les ménages n'investissent-ils pas plus dans la production (section 3) ? Pourquoi certains ménages ne conservent-ils pas plus de vivres pour la soudure [2] (section 4) ? Pourquoi la volatilité des prix au Sahel ne ressemble pas à la volatilité ordinaire des prix (section 5) ? La section 6 étudie des politiques de sécurité alimentaire et leur abstraction du contexte comportemental (elles postulent que les paysans ont intérêt à produire plus, à investir, à épargner).

2 Préférences pour le présent et sous-investissement agricole

L'épargne céréalière dans les villages ruraux du Burkina Faso est soumise à une forte pression sociale redistributive. Les redistributions sociales de vivres des ménages qui ont encore des stocks vers ceux qui n'en ont plus y ont un caractère pratiquement obligatoire. Refuser d'obéir aux règles sociales de redistribution, refuser d'aider un parent, même lointain, qui demande de l'aide, exposerait le ménage à de fortes difficultés sociales pour une très longue durée, jusqu'à l'isolement dans le village, des risques de réprésailles indirectes, etc. Cette pression pousse les ménages à différentes stratégies d'évitement, telles que la dissimulation de ressources (Jakiela and Ozier, 2016), ou la simulation de pauvreté (Baland et al., 2011). Mais cette pression sociale peut-elle également pousser à une consommation accélérée des ressources pour réduire la redistribution ? Goldberg (2017) donne des preuves très stimulantes de cette proposition, mais de manière expérimentale uniquement. Di Falco and Bulte (2011) montrent que les paysans en Afrique du Sud tentent de

1. hormis le curriculum vitae et l'introduction

2. La soudure est la période de l'année précédant les récoltes et où le grain de la récolte précédente peut venir à manquer. Il y a alors souvent pénurie et flambée des prix. La durée de la soudure varie d'une année à l'autre et d'un ménage à l'autre, mais dans l'Ouest du Burkina Faso, la soudure débute généralement entre avril et juin et se termine généralement en septembre.

convertir leurs ressources liquides en ressources immobilisées pour réduire la pression sociale sur leur ménage.

Contrairement aux impôts formels, ces redistributions sociales imposées sont soumises à la saisonnalité des besoins, car elles dépendent de la dynamique d'épuisement des stocks de céréales des parents. Plus la saison avance après la récolte, plus les ressources diminuent, et plus la pression sur ceux qui ont des stocks augmente. De ce fait, les incitations des ménages à réduire leur stock accessible sont fortes, et il peut être intéressant d'avoir un « empressement » relatif à réduire son stock afin de réduire la pression sur l'épargne de son ménage. C'est cet empressement que j'étudie, ou plus rigoureusement, les préférences temporelles, et non la pression sociale en tant que telle. La pression sociale crée un contexte favorable à l'empressement à consommer, elle permet de comprendre la préférence pour le présent autrement que comme une faiblesse (Goldberg, 2017).

La préférence pour le présent joue sur la dynamique de déstockage des réserves de céréales, nous allons le voir plus bas, mais elle joue aussi potentiellement en amont sur l'incitation à produire des stocks de céréales, pour les mêmes raisons. Derrière l'arbitrage entre maintenant et demain se cache l'arbitrage entre moi et les autres.

Les liens de causalité que nous établissons formellement relient les préférences temporelles mesurées à des comportements observés et qui conduisent à une insécurité alimentaire. Plus spécifiquement dans cette section, nous mesurons le lien entre les préférences temporelles et le faible investissement dans la production (utilisation d'engrais sur les céréales).

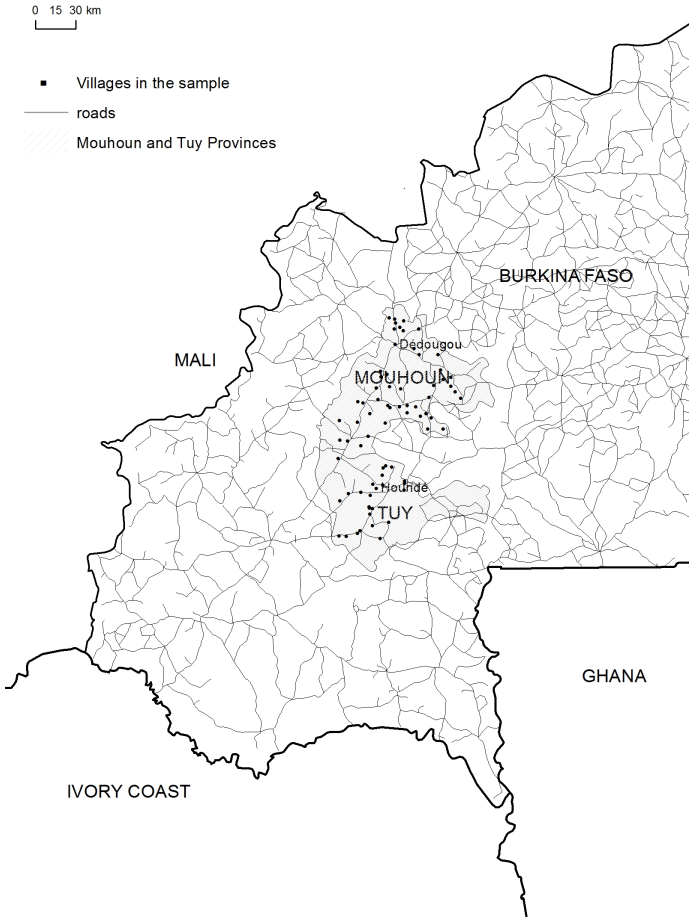
2.1 Préférence pour le présent et production de céréales

Le papier présenté dans cette sous section montre que les paysans de l'ouest du Burkina Faso ayant la plus grande préférence pour le présent utilisent moins d'engrais que les autres, et cultivent moins de maïs que les autres, à surface identique et à capital identique (Le Cotty et al., 2018). [3]

Dans le cadre du programme européen Farmaf, nous avons enquêté 1500 paysans répartis aléatoirement dans 73 villages aléatoirement distribués dans deux départements de l'ouest du Burkina Faso, le Tuy et du Mouhoun (figure 1). Avant la mise en oeuvre des éléments opérationnels du projet FARMAF, et en vue d'une étude d'impact du projet, nous avons interrogé tous les ménages de l'échantillon étudié, pour former la baseline de cette étude d'impact, avant mise en œuvre du projet. Ce sont les données de cette baseline qui sont utilisées dans ce papier.

3. Ce papier n'était pas prévu avant de collecter les données. Lorsque nous avons réalisé les mesures quasi-expérimentales des préférences temporelles et d'aversion au risque, nous suspections plutôt des relations entre les préférences temporelles et la vitesse de déstockage, car c'est l'intuition issue de nos premiers entretiens préalables en village. Mais la forte corrélation entre les préférences temporelles et la production et les engrais nous a poussé à étudier plus profondément cette corrélation, d'où ce papier.

FIGURE 1 – Location of farmers surveyed



Cette baseline incluait un module quasi-expérimental (gains hypothétiques) destiné à éliciter les préférences temporelles à la manière de Andersen et al. (2008) et l'aversion au risque à la façon de Holt and Laury (2002) , pour chaque chef de ménage. Pour l'élicitation de l'aversion au risque, les paysans sont placés face à des séries de choix à faire entre 2 loteries qui diffèrent par le niveau de risque et de gains espérés. Plus les paysans préfèrent les loteries d'espérance faible mais à probabilité de gains élevés, plus ils sont averses au risque. Plus ils préfèrent les loteries à espérance de gain élevé et à probabilité de gain faible, moins ils sont averses au rique. C'est leur série de choix qui révèle leurs préfèrences, pour obtenir une plus grande dispersion dans la mesure de l'aversion au risque. Nous avons répliqué l'expérience pour des gains modestes et pour des gains plus élevés.

Pour l'élicitation des préférences temporelles, les paysans font face à des séries de choix de gains hypothétiques d'autant plus élevés qu'ils sont lointains dans le future. Les paysans qui sont prêts à attendre pour obtenir des gains futurs élevés sont les paysans les plus patients, et ceux qui

préfèrent un gain plus faible sans attendre sont les moins patients (taux d'actualisation plus élevé). Là encore, c'est la série des réponses qui donne une mesure du taux d'actualisation. Cette mesure du taux d'actualisation est réalisée pour des arbitrages inter-temporels rapprochés (4 jours) et pour des arbitrages inter-temporels lointains (1 mois). La comparaison des deux mesures nous donne une mesure de l'incohérence temporelle des préférences. L'intuition est que certains personnes se pensent impatientes dans le futur proche, mais patientes dans le futur lointain. Ceci peut être interpreté comme une erreur de perception de leur capacité à épargner. Ce point sera développé dans la section 3.1 car cette incohérence temporelle ne donne pas de résultats significatifs ici.

Dans tous les travaux présentés ici comme dans la plupart de la littérature, ces préférences sont supposées être exogènes et prédéterminées. Bien que largement admise, cette hypothèse est lourde de conséquences dans l'analyse empirique. Si les préférences étaient en réalité déterminées par la conjoncture dans laquelle se situent les individus, plutôt que par des traits structurels de leur caractère, on ne pourrait plus interpréter les préférences comme des facteurs explicatifs des comportements. Néanmoins, comme les préférences individuelles sont élicitées hors contexte, dans un jeu, elles sont censées mesurer des traits de caractère structurels.

Une fois mesurées les préférences individuelles, nous tentons d'établir des relations statistiques avec les comportements agricoles des ménages. Dans cet article, nous établissons que les ménages ayant des préférences temporelles révélées plus fortes pour le présent sont ceux qui utilisent le moins d'engrais et produisent le moins de maïs. Cette relation est significative, et robuste aux 4 mesures différentes de la préférence temporelle que nous avons obtenues en faisant varier les gains et les délais de paiement. Les variables de contrôle utilisées corrigent pour les différences de capital, de surface, d'âge, de sexe, et de scolarisation.

Le modèle empirique estimé prend la forme générale

$$\textit{Engrais}_i = \alpha + \beta \textit{Aversion Risque}_i + \gamma \textit{Pref Temp}_i + \mathbf{C_i'}\theta + \eta_v + \varepsilon_i, \tag{1}$$

où Engrais$_i$ est la quantité d'engrais utilisée par le paysan i, *Aversion Risque*$_i$ est l'aversion au risque du paysan i et *Pref Temp*$_i$ est la préférence temporelle du paysan i. $\mathbf{C_i'}$ est un vecteur de variables de contrôle individuelles (surface totale cultivée, cheptel, nombre de volailles, nombre de charrues, sexe, age, scolarisation du chef du ménage, main d'oeuvre familiale, distance au marché, province)[4] ; η_v est une indicatrice du village.

On utilise trois mesures différentes de l'utilisation d'engrais : la quantité d'engrais NPK (Azote, Phosphore, Potassium) utilisée sur le maïs en kg d'engrais par hectare de maïs (*Dose*) ; la quantité d'engrais utilisée sur le maïs (*Quantité*) ; et la surface de maïs cultivée (*Surface en maïs*).

L'interprétation quantitative des résultats nécessiterait une présentation des statistiques descritives des diférentes variables et je me limite ici à la présentation des signes des coefficients. Il apparaît assez nettement que les plus impatients (taux d'actualisation ou discount rate élevé)

4. La culture du coton n'est pas incluse comme variable de contrôle ici car l'exogénéité de la culture du coton est sujette à discussion

utilisent moins d'engrais (table 1), et ils cultivent moins de maïs que les autres (table 2). Ce résultat est robuste à nos quatre mesures du taux d'actualisation (futur proche ou futur lointain, croisé avec des montants élevés ou des montants faibles). En revanche, l'aversion au risque ne semble pas affecter de manière significative la quantité d'engrais et le aurface cultivée en maïs.

TABLE 1 – Quantité d'engrais, aversion au risque et préférences temporelles

	[1] Quantité d'engrais (kg)	[2] Quantité d'engrais (kg)	[3] Quantité d'engrais (kg)	[4] Quantité d d'engrais (kg)
Aversion au Risque	4.25	5.86	4.72	6.21
	(5.29)	(5.29)	(5.22)	(5.38)
Taux d'actualisation	-47.56**	-48.11**	-155.58**	-157.24**
	(20.05)	(19.68)	(76.42)	(76.53)
Délai	1 mois	1 mois	4 jours	4 jours
Gains	faibles	élevés	faibles	élevés
Obs.	1502	1502	1502	1502

Note : les écarts types sont clusterisés au niveau village et sont entre parenthèses. * significatif à 10% ; ** à 5% ; *** à 1%. Toutes les regressions incluent des dummies village, la surface totale, le sexe, l'âge, la scolarisation, la main d'oeuvre, la province, le nombre de charrues, le cheptel et le nombre de volailles.

TABLE 2 – Surface en maïs, préférences temporelles et aversion au risque

	[1] Surface en maïs (ha)	[2] Surface en maïs (ha)	[3] Surface en maïs (ha)	[4] Surface en maïs (ha)
aversion au risque	0.04	0.02	0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
taux d'actualisation	-0.34*	-0.33**	-1.11**	-1.06**
	(0.15)	(0.15)	(0.52)	(0.52)
délai	1 mois	1 mois	4 jours	4 jours
Gains	faibles	élevés	faibles	élevés
Obs.	1502	1502	1502	1502

Note : les écarts types sont clusterisés au niveau village et sont entre parenthèses. * significatif à 10% ; ** à 5% ; *** à 1%. Toutes les regressions incluent des dummies village, la surface totale, le sexe, l'âge, la scolarisation, la main d'oeuvre, la province, le nombre de charrues, le cheptel et le nombre de volailles.

Un modèle agricole simplifié permet d'interpréter très directement cette relation. En début de soudure, les ménages ont un stock de ressource limité, d'une valeur B_0 et font face à un arbitrage : consommer un peu plus et investir un peu moins dans l'achat d'engrais, ou l'inverse. On note c_p la valeur de la consommation en période agricole et c_h la valeur de la consommation en période post récolte. Les deux consommations sont reliées par une fonction de production stochastique

$F(x, \xi)$ qui ne dépend que de l'engrais utilisé, x et d'un aléa ξ. La main d'oeuvre et la surface[5] sont considérées comme données.

Ainsi à la saison des cultures, le ménage achète de l'engrais pour une valeur x, et des biens de consommation (y compris l'autoconsommation) pour une valeur c_p, sous contrainte de ressources B_0. Par simplicité, le ménage épargne au cours de l'année, mais pas d'une année à l'autre.

Le ménage choisit la quantité d'engrais, et les niveaux de consommation qui maximisent son espérance d'utilité inter-temporelle CRRA (constant relative risk aversion).

$$\text{Max}_{c_p, c_h, x}\ EU = \frac{1}{1-r}\left(c_p\right)^{1-r} + \frac{1}{1+\delta}\frac{1}{1-r}E\left(\left(c_h\right)^{1-r}\right) \tag{2}$$

s.t.

$$c_p + x \leq B_0 \text{ (contrainte de budget de saison des cultures)}, \tag{3}$$

and,

$$c_h \leq F\left(x, \xi\right) \text{ (contrainte de budget après récolte)}. \tag{4}$$

Le paramètre r, mesure l'aversion au risque et δ mesure le taux d'actualisation (qui augmente avec l'impatience). F est croissante et concave en x , $F_x > 0$ and $F_{xx} \leq 0$.

La résolution de ce problème aboutit aux deux résultats :

[Usage d'engrais et impatience] : *la quantité optimale d'engrais décroît lorsque l'impatience augmente :*

$$\frac{\partial x^*}{\partial \delta} < 0.$$

[Usage d'engrais et aversion au risque] : *la quantité optimale d'engrais augmente avec l'aversion au risque pour les ménages suffisamment impatients : il existe $\widetilde{\delta} \geq 0$ tel que*

$$\frac{\partial x^*}{\partial r} \geq 0 \Leftrightarrow \delta \geq \widetilde{\delta}.$$

Bien qu'assez simple, cette analyse n'avait pas été faite auparavant, parce que l'utilisation d'engrais a beaucoup été reliée aux préférences pour le risque, plutôt qu'aux préférences pour le temps. Mais ce résultat a des conséquences en termes de développement agricole. Si on se borne à penser que le faible niveau d'utilisation d'engrais au Burkina vient de réticences face à l'innovation ou bien à des questions de technologie, ou même à un problème d'accès à l'engrais (ce qui est souvent mis en avant par les producteurs), plutôt d'un arbitrage temporel défavorable à l'investissement, on se coupe d'un pan de réflexion sur la déconnexion entre la période de disponibilité en ressource et la période d'investissement (voir à cet égard Duflo et al. (2011a)).

5. on peut supposer que lorsque la quantité d'engrais du maïs augmente, la surface de maïs augmente et la dose d'engrais est constante, et c'est alors la surface des autres cultures comme le mil et le sorgho qui diminuent, ou bien on peut supposer que toute la surface est cultivée en maïs et que c'est la dose d'engrais qui augmente quand la quantité d'engrais augmente, cela n'a pas d'incidence sur les résultats

2.2 Comment encourager l'investissement en période d'épuisement des ressources ?

Le résultat de ce papier est que dans la zone cotonnière du Burkina Faso, les exploitations les plus grandes ont la meilleure productivité de céréales à l'hectare, et ceci s'explique par le plus fort accès aux engrais à crédit permis par la culture du coton. Ce n'est pas le prix de l'engrais qui permet d'accroître son utilisation, mais le fait de pouvoir investir en période de soudure et de payer cet investissement en période de récolte. L'article correspondant à ce résultat est Bazié et al. (2020).

Il existe de nombreuses études montrant que les exploitations plus petites sont les plus productives, pour deux raisons principales : la qualité des sols serait meilleure dans les exploitations plus petites et les défaillances de marché de la terre, du capital et du travail pénaliserait les plus grandes exploitations (Barrett et al., 2010). La gestion du risque a également été avancée comme une raison de cette relation inverse (Barrett, 1996).

D'autres études montrent que cette relation inverse taille-productivité est parfois une relation erronée, due à des différences d'intenstification (Wassie et al., 2019; Carter, 1984) ou à des erreurs de mesures (Abay et al., 2019). Mais il est rare de trouver dans la litérature des cas, y compris théoriques, où la relation entre la surface agricole et la productivité de la terre est positive. Puisque les rendements sont le plus souvent constants (si tous les facteurs augmentent en même proportion, la production s'accroît de la même proportion), la production augmente le plus souvent comme la surface, si tous les facteurs de production sont variables, ou moins vite que la surface, si l'un au moins des facteurs de production est fixe.

Feder (1985) fournit une exception notable de l'agriculture salariale, dans le cas où il existe des économies d'échelle réalisées dans la supervision du travail.

Au Burkina Faso, dans la zone cotonnière, cette relation est positive à la fois en coupe transversale si l'on compare les exploitations entre elles, et en coupe longitudinale si on compare l'évolution des exploitations.

FIGURE 3 – Evolution de la relation entre la surface totale cultivée (en ha) et la productivité des céréales (en kg /ha) au Burkina Faso (régression de moyennes par province et par an)

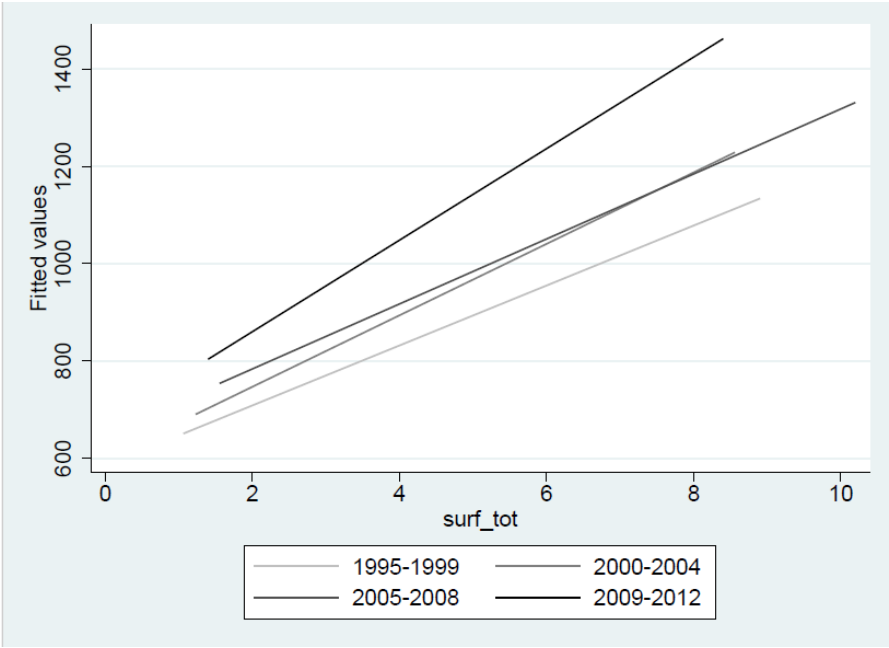
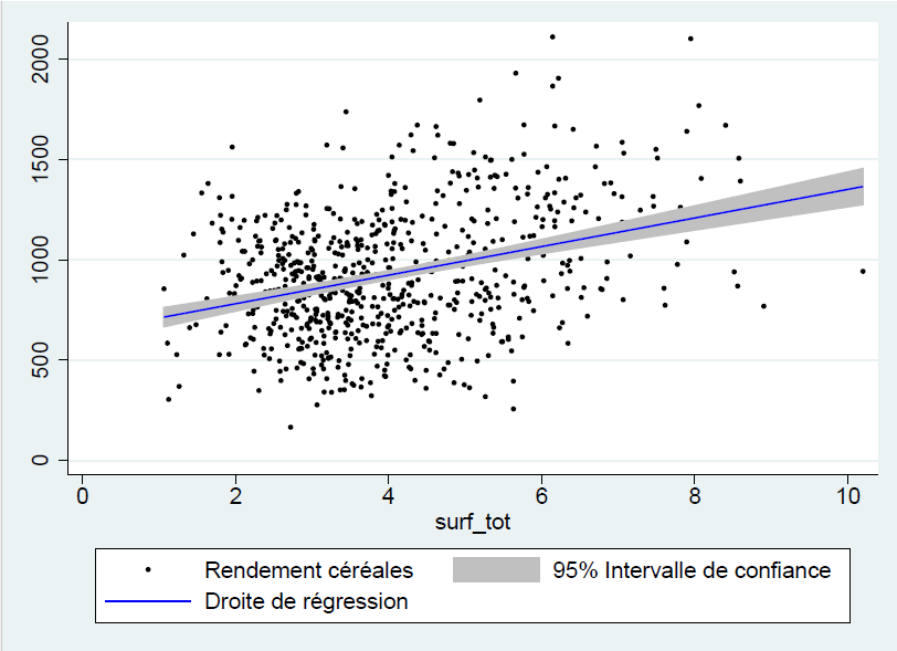


FIGURE 2 – Relation entre la surface totale cultivée (en ha) et la productivité des céréales (en kg /ha) au Burkina Faso (moyennes par province et par an)



L'explication est que les contraintes de liquidité et de crédit en début de soudure sont tellement

fortes qu'elles suffisent à expliquer en grande partie le faible niveau d'utilisation d'engrais. Les sociétés cotonnières fournissent de l'engrais à crédit aux producteurs de coton et se remboursent lors de la livraison du coton. Et les exploitations les plus grandes cultivent plus de coton, et ont accès à un crédit engrais plus élevé pour la production du coton, mais aussi pour la production du maïs. Cette relation positive entre la taille des exploitations et la productivité de la terre est développée à la fois théoriquement et empiriquement dans cet article.

Le modèle proposé pour analyser cette relation est inspiré de Feder (1985). Chez Feder, le travail salarié est l'input principal, mais dans notre cas, la quantité d'engrais utilisée est l'input principal de la production de maïs, que l'on cherche à expliquer. Dans notre analyse, nous considérons deux productions, le maïs et le coton. Pour simplifier, on suppose que la production de chaque culture est séparable du point du vue technologique et à rendements constants (la taille de l'exploitation agricole en tant que telle n'a pas d'effet sur les rendements si tous les facteurs de production augmentent dans les mêmes proportions que la surface). A même dose d'engrais par hectare, une exploitation de un hectare a les mêmes rendements qu'une exploitation de deux hectares. Si les rendements augmentent entre une exploitation de 1 et de 2 ha, c'est donc que l'exploitation de deux ha met plus d'engrais à l'hectare. Cela permet de ne pas présupposer que par elle-même, la taille joue sur le rendement. Une telle technologie à rendements constants implique que les fonctions de production peuvent être ramenées à des fonctions de production à l'hectare, $\frac{Y^c}{S^c} = y^c = g(x^c)$; $\frac{Y^m}{S^m} = y^m = f(x^m)$, où les x^i sont les doses d'engrais à l'hectare, S^c est la surface en coton et S^m est la surface en maïs.

La culture du mais peut utiliser de l'engrais acheté par les producteurs sur le marché, mais pour simplifier le papier, nous considérons que l'ensemble de l'engrais pour la culture du maïs $x^m S_m$ est fourni par la société cotonière (Sofitex), mais seulement aux producteurs de maïs qui produisent aussi du coton. La quantité fournie par les sociétés cotonnières pour le maïs est plafonnée en fonction de la surface en coton, $x^m S^m \leq \alpha S^c$. Le coton requiert également de l'engrais $x^c S^c$ fourni par les sociétés cotonières en proportion de la surface cultivée en coton, $x^c \leq \gamma$. En pratique, le seul cas pertinent est celui où les producteurs utilisent tout l'engrais disponible et la fonction de production du coton ne dépend alors plus que de la surface en coton puisque le producteur agricole ne choisit pas le degré d'intensification : $y^c S^c = g(\gamma) S^c$. Au Burkina Faso, en pratique, $\alpha = 1$ et $\gamma = 3$ lorsque les quantités d'engrais sont exprimées en nombre se sac de 50 kg de NPK et les surfaces exprimées en hectare. Enfin, la surface cultivée en coton est elle même limitée par négociation au sein des groupements de producteurs de coton qui contractent le crédit. L'enjeu de cette limitation est d'éviter de cultiver de trop grandes surfaces de coton, en obtenant un crédit trop important par rapport à la capacité des ménages à le cultiver suffisamment bien pour rembourser le crédit. Mais il s'agit d'une contrainte floue et nous n'en tenons pas compte dans ce modèle. Enfin, nous supposons que la production de coton n'est possible qu'à partir d'une certaine superficie. Les plus petites exploitations ne font que du maïs pour nourrir leur famille sans prendre le risque de produire une culture de rente, et sans acheter d'engrais, et à partir d'une certaine taille elles commencent à semer du coton parallèlement à leur maïs. Cette hypothèse correspond à une réalité empirique (figure 5).

Le programme du producteur s'écrit :

$$\max_{x^m,x^c,S^m,S^c} \pi = p^c y^c S^c + p^m y^m S^m - w(S^c x^c + S^m x^m)$$
$$S^c + S^m \leq S$$
$$(S^m \geq \underline{S}^m) S^c \geq 0$$
$$S^m x^m \leq \alpha S^c$$
$$S^c x^c \leq \gamma S^c$$
$$y^m = f(x^m)$$
$$y^c = g(x^c) \tag{5}$$

La variable w est le prix de marché de l'engrais supposé identique au prix de fourniture de l'engrais par les sociétés cotonnières, S est la surface cultivable du ménage.

La deuxième contrainte traduit le passage de l'agriculture de subsistence à la coexistence coton-maïs. Le seuil $\underline{S}^m$ est la surface de maïs minimale pour commencer à faire du coton. Si $S^m \geq \underline{S}^m$, alors S^c peut être positif strictement, maïs si $S^m < \underline{S}^m$, on a nécessairement $S^c = 0$.

Les troisième et quatrième contraintes sont les contraintes sur les engrais fournis par la Sofitex.

Sans détailler la résolution de ce problème, elle aboutit à trois domaines de solutions, illustrés par la figure 4 qui représente l'effet théorique d'un accroissement de la surface cultivée sur les choix du producteur en matière de surface en coton, de dose d'engrais sur le maïs, et donc de rendement.

Dans la partie gauche de chacun des trois schémas correspondant à ces choix, lorsque $S < \underline{S}^m$, la surface totale est trop faible pour que le ménage puisse produire du coton et toute sa surface est consacrée aux céréales. Il n'utilise pas d'engrais et le rendement du maïs ne varie pas avec la surface totale.

Dans la partie intermédiaire où $\underline{S}^m < S < \underline{S}^m + \underline{S}^c$, le ménage consacre tout l'accroissement de sa surface à la culture du coton. La pente de la droite sur ce segment est égale à 1, et $\underline{S}^c$ est la surface de coton minimale à partir de laquelle le rapport des surfaces devient optimal (et la surface de maïs recommence à augmenter). L'idée est que les ménages concernés rattrapent l'optimum économique le plus 'vite' possible, or cet optimum se caractérise dans notre modèle par une plus grande proportion de coton (θ^*). L'utilisation d'engrais pour le maïs augmente avec S car S^c augmente plus vite que S en valeur relative ($x^m = \alpha \frac{S^c/S}{1-S^c/S}$). Le rendement du maïs augmente avec x^m.

Dans la partie de droite, $S > \underline{S}^m + \underline{S}^c$, le ménage a maintenant "retrouvé" sa proportion optimale de coton/maïs et les deux surfaces augmentent en proportion fixe. La dose d'engrais du maïs devient constante et le rendement du maïs aussi.

FIGURE 4 – solution globale

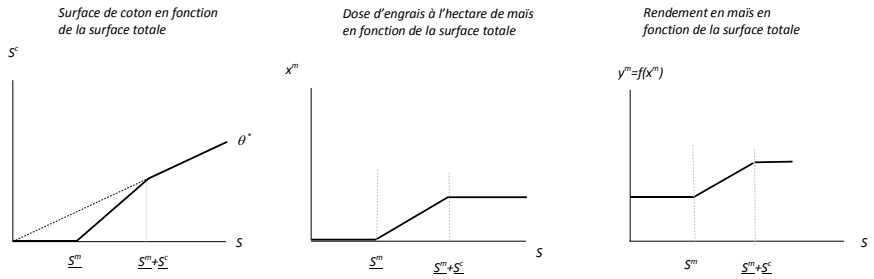
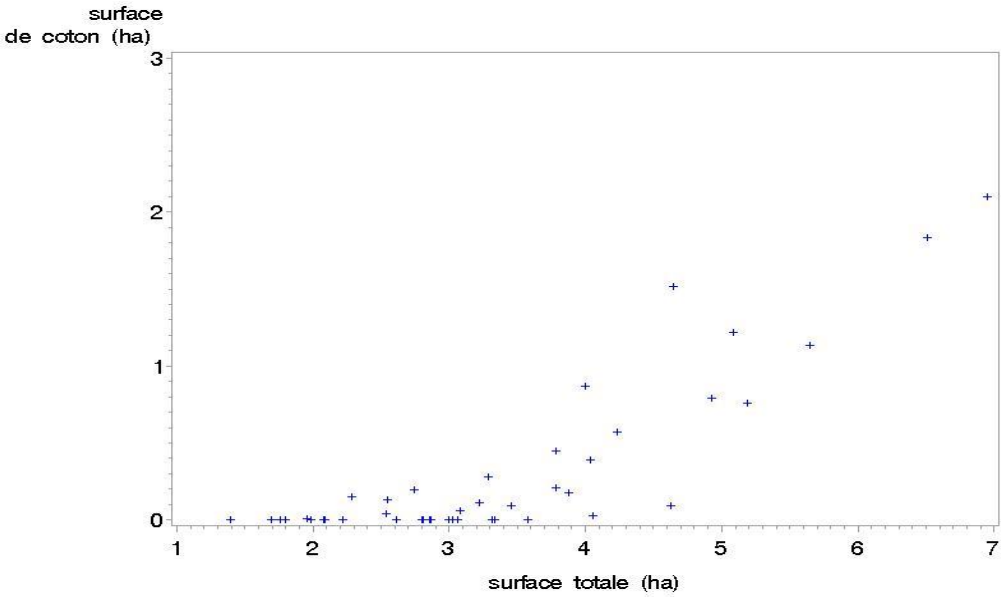


FIGURE 5 – contrepartie empirique de la surface de coton en fonction de la surface totale, année 2010



En théorie donc, l'effet attendu de la surface cultivée sur la productivité du maïs devrait être nul pour les petites surfaces, positif pour les moyennes surfaces, et nul pour les surfaces plus élevées. On voit sur la figure 5 que ce dernier cas n'a apparemment pas une grande importance empirique, mais même si c'était le cas, en linéarisant l'effet de la surface sur la productivité, l'effet attendu moyen sur l'ensemble de la population serait positif.

L'estimation empirique proposée est l'effet de la surface totale sur la productivité globale des céréales ainsi que sur la productivité partielle du maïs, du mil et du sorgho, à partir de données de l'enquête permanente agricole du ministère de l'agriculture du Burkina Faso, de données pluviométriques publiques annuelles par province et de données publiques de prix mensuels par province (Sonagess). L'enquête recueille chaque année les données de 4500 ménages pendant 16 ans entre 1996 et 2012 répartis dans 45 provinces dont 38 sont exploitables du point de vue de la continuité des données. Finalement, nous constituons un panel de 38 ménages moyens représentatif des provinces, observés pendant 16 ans, 38 prix annuels et 38 pluviométries annuelles pendant 16 ans.

Les résultats sont résumés dans la table 3.

TABLE 3 – Estimation de l'effet de la taille des exploitations sur les rendements des céréales par la méthode des moments généralisés de Arrellano et Bond

	céréales	maïs	mil	sorgho
	(1)	(2)	(3)	(4)
constante	18,16 ***	5,63	16,80 ***	10,06 **
	(3,32)	(0,58)	(3,42)	(1,87)
rendement décalé	0,00	-0,14	-0,09	-0,06
	(-0,01)	(-1,51)	(-1,47)	(-1,01)
surface cultivée	34,24 ***	45,43 **	22,60 **	20,27 **
	(3,09)	(2,46)	(2,32)	(1,92)
existence de coton	190,97 ***	588,55 ***	144,58	205,72 **
	(1,48)	(2,63)	(1,30)	(1,65)
cumul pluviométrique	0,25 ***	0,02	0,28 ***	0,32 ***
	(3,32)	(0,14)	(4,08)	(4,34)
prix du maïs	2,16	6,72 **	4,88 ***	5,75 ***
	(1,19)	(2,12)	(2,94)	(3,28)
prix du mil	12,92 ***	13,20 ***	2,50	3,04
	(4,70)	(2,82)	(1,03)	(1,14)
prix du sorgho	-12,74 ***	-15,70 **	-4,64	-5,43
	(-3,54)	(-2,52)	(-1,44)	(-1,55)
Nombre de provinces	38	38	38	38
Longueur des séries temporelles	16	16	16	16

t test entre parentheses

* $(p < .1)$, ** $(p < .05)$, *** $(p < .01)$

Les rendements de céréales sont donc très positivement liés à la surface totale via la culture du coton. Ainsi, si le coton est une culture décriée (par des ONG et de nombreux producteurs eux-mêmes) en raison de sa faible rentabilité les années de prix bas, il a une utilité bien réelle sur les céréales, via l'utilisation sur le maïs de l'engrais fourni à crédit par la société cotonnière.

3 Biais pour le présent et déstockage précoce

3.1 Biais pour le présent, épuisement des ressources, et stockage bloqué (warrantage)

Ce papier montre que les paysans ayant le plus fort biais pour le présent (incohérence temporelle propice à une désépargne plus rapide que l'optimum) sont ceux qui utilisent le plus un mécanisme de stockage autocontraignant (ou self control) qu'on leur propose (le warrantage) et qui les pousse à retarder l'épuisement des ressources alimentaires (Le Cotty et al., 2019).

L'idée du papier est d'explorer si les préférences temporelles peuvent expliquer la soudure , et si le warrantage peut s'interpréter comme un mécanisme d'atténuation de l'insécurité alimentaire en soudure. En effet, une littérature florissante sur les préférences temporelles biaisées vers le présent tented d'expliquer un grand nombre de comportements sous optimaux, en particulier de surconsommation et de sous épargne. Les agents ayant ce type de préférences consomment leurs ressources plus rapidement qu'ils ne le souhaitent parce qu'ils ont tendance à s'accorder une "dérogation" pour le présent, en pensant qu'ils épargneront plus à la prochaine décision, mais lorsque vient le temps de cette prochaine décision, ils s'accordent à nouveau la même dérogation pour le présent. Appliquée à la consommation du stock de céréales par les ménages sahéliens, cette idée pourrait-elle expliquer la soudure ? et si oui, existe-il un mécanisme volontaire pour y remédier ? C'est l'idée que nous avons voulu éprouver dans ce papier.

Avant de replacer notre papier dans la littérature sur les préférences incohérentes, rappelons que la majorité de la littérature économique en analyse dynamique suppose que les préférences temporelles sont les facteurs d'actualisation exponentiels, car ce sont les seuls qui aboutissent spontanément à des plans de consommation cohérents (les agents ont un rythme de consommation conforme à leur plan). Avec un facteur d'actualisation exponentiel, un ménage agricole du Burkina Faso consomme chaque mois une certaine quantité de son stock, selon une dynamique qu'il a choisie et qu'il respecte (dynamique optimale au sens de la maximisation d'utilité intertemporelle décidée au début de la constitution du stock). Cette consommation est plus forte en période d'abondance juste après la récolte, et de moins en moins forte à mesure que le stock restant diminue. Cela signifie que la consommation journalière se réduit au fil du temps, mais cette réduction reflète simplement une préférence pour le présent, ou impatience classique. Plus les individus sont impatients, à contraintes identiques, et plus ils épuiseront leur stock plus vite. Mais ce différentiel ne traduit pas d'incohérence, il traduit des préférences individuelles classiques.

Mais plusieurs éléments empiriques nous indiquent que le plan de consommation réel des ménages n'est pas un plan de consommation optimal répondant à un taux d'actualisation exponentiel tel que défini plus haut, et la décroissance de la consommation semble plus rapide qu'à l'optimum. D'abord, les paysans rencontrés nous ont très souvent exprimé qu'ils consomment trop en période post-récolte et le regrettent ensuite. "On ne peut pas s'en empêcher." "Heureusement nos femmes nous surveillent et cela nous oblige à limiter les dépenses de récolte". Par ailleurs, la soudure est un phénomène très généralisé au Sahel, y compris les bonnes années. Ensuite, le rythme de réduction des stocks, s'il répondait à un plan de consommation cohérent, correspondrait à des taux d'actualisation extrêmement élevés, donc des niveaux d'impatience très élevés. Enfin, la sou-

dure est souvent meurtrière au Sahel, engendre de la mendicité intra et extra-familiale, parfois de l'exode, même si la consommation post-récole a été bonne et il est donc difficile d'imaginer qu'elle corresponde à un plan optimal.

Nous avons donc imaginé que comme il a été observé dans de nombreux comportements humains, des préférences biaisées vers le présent puissent expliquer le déstockage accéléré des ressources.

Strotz (1956) est le premier économiste à avoir exposé et formalisé cette idée, et la nombreuse littérature qui s'en est suivie a consisté dans une grande mesure à adapter cette idée à différents cas, à en affiner la formalisation, et plus récemment, à démontrer empiriquement sa pertinence à travers l'économie comportementale. Strotz avait déjà formalisé l'idée que le "precommitment" (engagement contraignant) était la solution théoriquement choisie par les agents à préférences incohérentes pour restaurer leur optimum. Les agents biaisés vers le présent contraignent leurs choix futurs proches pour protéger les possibilités de consommation de leur futur lointain. Strotz (1956) interprète l'incohérence temporelle comme une distorsion de la perception du temps. Cette incohérence temporelle conduit les agents à adopter une dynamique de consommation plus rapide que ce qu'ils pensaient adopter même si rien ne change dans les paramètres objectifs de l'environnement.

Mais dans cette conception de l'incohérence temporelle, il n'est pas simple d'admettre que les agents reproduisent plusieurs fois la même erreur de prédiction sur eux-mêmes, comme s'ils n'apprenaient pas d'eux-mêmes. C'est qu'il ne s'agit en réalité pas d'une erreur de connaissance de soi, mais plutôt d'une sorte de lutte intérieure entre ce que l'on voudrait faire dans le futur, et ce que l'on va vraiment faire. Une lutte dont le consommateur présent a tendance à sortir vainqueur à chaque période par rapport au consommateur plus vertueux qu'il avait imaginé (« demain j'arrête de fumer mais aujourd'hui je fume, demain je réduis le sucre mais aujourd'hui je m'accorde une dernière patisserie, demain je termine mon HDR mais aujourd'hui je réfléchis encore un peu, etc. »). C'est dans cette ligne que s'est développée l'interprétation plus psychologique de l'incohérence temporelle, en rapport avec l'impulsivité (Ainslie, 1975) ou les désaccords entre soi-multiples (Ainslie, 1986).

Puis Akerlof (1991) a formalisé l'idée de procrastination, qui a ensuite été étendue à de nombreux comportements relatifs à la gestion des efforts dans le temps (cf par exemple Duflo et al. (2011b)). Loewenstein and Prelec (1992) proposent un cadre formel plus large d'analyse des anomalies d'arbitrages intertemporels.

Le precommitment, aujourd'hui plutôt appelé commitment, concerne ceux que O'Donoghue and Rabin (2015) appellent les sophistiqués, qui savent qu'ils ne feront pas ce qu'ils projettent. Pour eux, s'il existe une façon de s'obliger à respecter leur plan de consommation, un mécanisme de self control, ils le font, et évitent ainsi l'épuisement des ressources. La réflexion sur les mécanismes concrets permettant à ce type d'agents, avec des préférences biaisées vers le présent mais désireux de corriger le biais de comportement qu'elles entraînent, s'est développée notamment avec Laibson (1997); O'Donoghue and Rabin (1999); Gul and Pesendorfer (2001). Mais c'est l'apport de l'économie expérimentale qui a réellement permis d'accroître l'importance et la crédibilité de ces théories en montrant l'existence d'un lien empirique entre ce type de préférences et l'adoption de mécanismes de self contrôle Ashraf et al. (2006); Bauer et al. (2012).

Du point de vue de l'analyse de la soudure, certains paysans semblent avoir un biais vers le présent, semblent se connaître, et semblent savoir qu'ils ne feront pas ce qu'ils prévoient de faire. Mais peut-on le montrer ?

Dans le cadre du projet européen FARMAF(Farm Risk Managmenet in Africa) entre 2012 et 2016, nous avons mis en place dans 8 villages un mécanisme de warrantage des céréales, une forme de stockage contraignant conduisant à un self control dans l'arbitrage consommation/épargne. Le principe du warrantage est le suivant. Au moment de la récolte, les producteurs peuvent stocker une partie de leur récolte dans un entrepôt collectif, (le "magasin") financé et construit dans le cadre du projet, et qui sera fermé à clé pendant 6 mois, et qu'ils ne pourront pas ouvrir avant. Une fois prise leur décision de stocker ils ne pourront plus revenir dessus. Un réseau de microfinance (les caisses populaires) propose un crédit facultatif d'un montant inférieur ou égal à 80% de la valeur du stock immobilisé. Ce crédit peut être utilisé pour des activités agricoles ou pour la consommation, et doit être remboursé avant ouverture du magasin, ou, avec l'accord de la caisse de micro finance, le jour de l'ouverture du magasin en cas de vente groupée en présence de l'acheteur au village ce jour là. Le plus souvent, les prix montent entre le moment du stockage (novembre ou décembre) et le moment du déstockage (mai ou juin), ce qui couvre le risque pour l'organisme de microfinance, et permet au producteur de ne pas trop vendre à la récolte lorsque les prix sont bas. A cause de cet effet de hausse des prix et d'accès au crédit, le warrantage a surtout été étudié pour ses effets de rentabilité comptable, mais pas pour ses effets d'épargne auto-contraignante, ou self-control.

Le warrantage a été mis au point dans les années 1990 au Niger et à Madagascar. Il ne visait pas à jouer ce rôle d'épargne auto-contraignante, mais essentiellement à fournir un collatéral à des institutions de microfinance en l'échange d'un crédit octroyé à la période de récolte. Avec le temps, au Burkina Faso, la fonction d'épargne forcée a pris de plus en plus d'importance, même si la fonction de crédit demeure importante. Dans notre projet Farmaf, les 8 villages bénéficiaires de ces entrepôts ont reçu d'intensives séances de sensibilisation, échanges, voyages d'étude, formations entre 2012 et 2014. En 2012, avant le démarrage du warrantage, nous avons enquêté de manière aléatoire un échantillon de 900 ménages dans ces villages, sans savoir qui allait adopter le warrantage. Nous avons posé aux chefs de ménage des questions hypothétiques tirées d'expériences économiques avec incitations, afin de mesurer l'aversion au risque de chaque individu, et les préférences temporelles de chaque individu (voir la section 2.1). Nous avons également enregistré un certain nombre de variables de contrôle et d'output. En 2016, nous avons réenquêté le même échantillon, et nous avons en plus enregistré la participation au mécanisme de warrantage. Nous avons constaté qu'en moyenne, ceux qui utilisent le plus le warrantage sont ceux qui ont le plus de biais pour le présent. Ceci tend à confirmer que le warrantage est utilisé comme un mécanisme d'épargne forcée par les individus les plus enclins à consommer trop vite leurs ressources.

Nous avons développé un modèle de soi-triples à 3 périodes qui reprend les principales caractéristiques du warrantage, et nous montrons que l'équilibre de Nash préféré par le soi-initial est celui qui utilise le warrantage pour contraindre le soi intermédiaire à laisser plus de céréales au soi de soudure (voir Fudenberg and Levine (2006).)

L'exposé formel du modèle étant un peu long, nous en présentons ici seulement les ingrédients essentiels et le principe de sa résolution. Le jeu est un jeu non coopératif entre le soi initial et le soi

intermédiaire. Le soi de soudure ne joue pas, il ne fait que constater les resources que lui a laissées le soi intérmédiaire. Les 3 périodes sont la période de récolte, où le producteur choisit combien il consomme, combien il dépose en warrantage, et quel crédit il demande ; la période de stockage, dans laquelle le producteur choisit la quantité qu'il consomme (sous contrainte de disponibilité hors warrantage), et la période de soudure, durant laquelle le producteur consomme le reste. Le producteur de période 1 joue contre le joueur de période 2 et le jeu se résout comme un équilibre de Nash parfait en sous jeux, en commençant par la fin (backward induction subgames perfect Nash equilibrium). Puisque le producteur a une préférence temporelle biaisée vers le présent, ça signifie qu'il souhaite s'accorder une dérogation en période 1 pour consommer plus que le rythme futur, mais qu'il ne souhaite pas s'accorder cette dérogation en période 2. Mais le joueur 2 va aussi s'accorder cette dérogation, ne respectant pas le souhait du joueur 1. Comme le joueur 1 sait que le joueur 2 a l'intention de s'accorder cette dérogation, il va chercher à contraindre ses possibilités de consommation, grâce au stockage à 6 mois du warrantage. Ce qui complique le problème, est que la possibilité de crédit, qui sera disponible au joueur 2, accroît la marge de manœuvre du joueur 2 que le joueur 1 cherche à réduire. Mais comme le crédit n'est que de 80% de la valeur du stock au plus, et comme le crédit est facultatif, il est toutefois possible au joueur 1 de contraindre le joueur 2.

La résolution en backward induction se passe ainsi : étant donné la quantité consommable que lui laissera le joueur 1, le joueur 2 maximise la somme de son utilité de période 2 et de l'utilité actualisée de la troisième période. Ceci donne une formule de consommation de période 2 vraie quelle que soit la quantité du stock disponible laissée par le joueur 1. Autrement dit, cela donne la stratégie du joueur 2. Le joueur 1 intègre cette stratégie dans la maximisation de la somme pondérée de ses utilités de période 1, 2 et 3, en remplaçant la consommation du joueur 2 par sa stratégie (expression fonction de la consommation du joueur 1). C'est cette maximisation qui donne l'optimum.

Le résultat principal est que si le warrantage est comptablement suffisamment intéressant, tout le monde l'utilise quelles que soient les préférences temporelles. Mais si sa rentabilité espérée (car les prix sont stochastiques) est faible, seuls les gens dont la préférence est suffisamment biaisée vers le présent utilisent le warrantage pour contraindre leur consommation de deuxième période.

Les estimations empiriques confirment ce résultat. Les producteurs ayant des préférences temporelles avec le plus fort biais vers le présent, d'après leurs réponses aux questions inspirées d'économie expérimentale sans incitation, sont également ceux qui utilisent le plus le warrantage, à la fois en probabilité de faire du warrantage (modèle probit) et dans une moindre mesure en quantité stockée (modèle tobit).

Il est dificile de comprendre un tableau de résultat brut indépendamment des statistiques descriptives et du modèle estimé, mais simplement pour montrer les écarts de précision entre les estimateurs des coefficients des préférences ordinaires et de l'estimateur des préférences hyperboliques (i.e. biaisées vers le présent ou biaisées vers le futur proche au détriment du futur lointain), nous présentons néanmoins le résultat du modèle probit.

TABLE 4 – participation au warrantage : modèle probit

	(1)	(2)	(3)	(4)	(5)
aversion au risque (r)	0.000	-0.013	-0.013	0.015	-0.035
	(0.053)	(0.053)	(0.053)	(0.077)	(0.075)
	[0.997]	[0.685]	[0.685]	[0.790]	[0.472]
taux d'actualisation (δ)	-0.350	0.205	0.195	0.319	0.138
	(0.321)	(0.384)	(0.386)	(0.588)	(0.509)
	[0.328]	[0.801]	[0.808]	[0.599]	[0.873]
pref hyperbolique (h)		1.769***	1.984**	1.971**	1.655**
		(0.633)	(0.907)	(1.016)	(0.802)
		[0.092]	[0.082]	[0.224]	[0.047]
pref hyperbolique x 2015			-0.013		
			(0.263)		
			[0.280]		
effet fixe Village-par-Année	yes	yes	yes	yes	yes
Nb. obs.	1,149	1,149	1,149	653	496
année	2013 & 2015	2013 & 2015	2013 & 2015	2013	2015
variables de contrôle					
charrues	-0.020	-0.024	-0.024	-0.010	-0.039
	(0.045)	(0.046)	(0.046)	(0.066)	(0.063)
	[0.732]	[0.677]	[0.673]	[0.915]	[0.434]
main d'oeuvre	-0.022	-0.022	-0.022	-0.032	-0.012
	(0.014)	(0.014)	(0.014)	(0.021)	(0.019)
	[0.080]	[0.070]	[0.070]	[0.059]	[0.351]
scolarisation	0.395***	0.408***	0.408***	0.432***	0.390***
	(0.099)	(0.100)	(0.100)	(0.145)	(0.139)
	[0.002]	[0.002]	[0.002]	[0.024]	[0.009]
age	-0.006*	-0.006*	-0.006*	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
	[0.189]	[0.187]	[0.187]	[0.353]	[0.141]
Sexe	-0.034	-0.160	-0.160	0.142	-0.385
	(0.324)	(0.325)	(0.324)	(0.542)	(0.448)
	[0.955]	[0.845]	[0.851]	[0.787]	[0.673]
surface totale	0.071***	0.071***	0.072***	0.072***	0.072***
	(0.012)	(0.012)	(0.012)	(0.016)	(0.017)
	[0.001]	[0.001]	[0.001]	[0.007]	[0.009]
cheptel (moins de 10)	0.422***	0.439***	0.440***	0.510***	0.398***
	(0.141)	(0.142)	(0.142)	(0.209)	(0.195)
	[0.066]	[0.059]	[0.059]	[0.046]	[0.065]
cheptel (plus de 10)	0.252	0.279	0.279	0.484	0.099
	(0.223)	(0.224)	(0.224)	(0.316)	(0.314)
	[0.557]	[0.505]	[0.499]	[0.367]	[0.775]
volaille	0.001	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
	[0.876]	[0.862]	[0.863]	[0.793]	[0.988]

Note : *** (resp. **, *) indiquent le rejet de l'hypothèse nulle d'absence d'impact aux seuils de 1% (resp. 5%, 10%) de significativité. Les p-values calculées par la méthode des scores bootstrap après clustering au niveau village sont présentées entre crochets (Kline and Santos, 2012).

Le warrantage était connu comme un outil permettant de réduire la soudure, et reconnu comme tel par de nombreux paysans, et nous avons mis en évidence une explication supplémentaire ici.

3.2 Evaluation d'impact d'une politique de stockage bloqué (warrantage) sur la production et la sécurité alimentaire

Nous avons monté un RCT (randomized controlled trial ou essai randomisé contrôlé) au Burkina Faso pour mesurer l'impact du warrantage et nous montrons que (i) les ménages des villages aléatoirement sélectionnés pour en bénéficier (ITT analysis, Intention To Treat analysis) ont accru nettement la production, les engrais, le capital animal et la disponibilité de mil avant la soudure et (ii) les ménages participant au programme (ATT, Average Treatment effect on the Treated) ont en outre une meilleure sécurité alimentaire en soudure. Ce travail est en cours d'évaluation et non publié à ce jour (Le Cotty et al., 2020).

Le RCT a consisté à sélectionner aléatoirement 8 villages dans une liste de 17 villages présentant des caractéristiques objectives compatibles avec la réalisation du warrantage, notamment l'existence d'une caisse de microfinance à proximité, la non opposition du village à l'introduction au warrantage dans leur village. Le fait de tirer au sort des villages plutôt que des individus réduit nettement les chances que les villages témoins et les villages bénéficiaires aient des caractéristiques identiques au départ, et ce qui réduit la précision de l'impact mesuré par la comparaison des villages (ITT). Mais le tirage de villages présente un avantage décisif, c'est d'éliminer la contamination des témoins par le traitement. Lorsqu'on tire au sort des individus bénéficiaires du warrantage, on est presque certain que les non bénéficiaires vont en bénéficier par transfert de sacs de céréales. La comparaison des traités et des témoins va donc considérablement réduire l'impact mesuré. En revanche, les villages non bénéficiaires qui n'ont pas d'entrepôts de stockage ne bénéficient effectivement pas du warrantage, ou de manière très anecdotique [6] .

Par ailleurs, le tirage aléatoire des villages, même en petits nombres, permet une mesure de l'impact sur les participants (ATT) qui utilise le fait d'appartenir à un village bénéficiaire comme instrument d'être un ménage qui participe au warrantage.

La sélection des villages bénéficiaires a eu lieu en 2012, les entrepôts ont été construits en 2013 et les premières formations ont eu lieu en 2013 après la baseline, une enquête de 900 villageois réalisée en janvier et février 2013 pour enregistrer à la fois leurs préférences individuelles des chefs de ménage mais aussi les principales variables de leur activité agricole. Le warrantage a démarré après la récolte 2013 pour les ménages intéressés. J'ai mené plusieurs formations, séances de questions-réponses, débriefing après stockage, avec notre partenaire opérationnel, la confédération paysanne du Faso, dans tous les villages bénéficiaires. J'ai également assuré la mise en relation des responsables villageois du warrantage avec les responsables des caisses populaires, afin de dépasser les appréhensions des paysans à aller rencontrer les banquiers, et pour que chaque partie exprime à l'autre ses attentes et son calendrier. L'anticipation des dates pour une bonne vitesse de réaction de la banque est un paramètre fondamental de réussite, sous-estimé dans de nombreux

6. Par ailleurs, le sentiment d'inéquité qui peut suivre un tirage au sort individuel peut perturber l'expérience ou nécessiter une indemnisation des ménages témoins. C'est moins problématique au niveau des villages.

programmes de warrantage, au Burkina et dans tout le Sahel. Un crédit tardif est synonyme de warrantage raté (prix élevés au stockage, donc marge financière faible, risque financier élevé, volume stockage plus faible, etc.). Il est fondamental que les paysans anoncent très tôt à la banque leur volume à stocker et leur demande de crédit pour que la banque débloque le crédit précocément. il est donc fondamental que les paysans soient à l'aise avec leur interlocuteur à la caisse populaire, ce qui n'est pas le cas par défaut.

En 2016 nous avons ré-enregistré les principales variables de l'activité agricole à la même période (janvier-février) ainsi que de nouvelles variables spécifiques à la sécurité alimentaire en soudure (août).

La participation se résume ainsi (figure 6).

FIGURE 6 – Sample composition

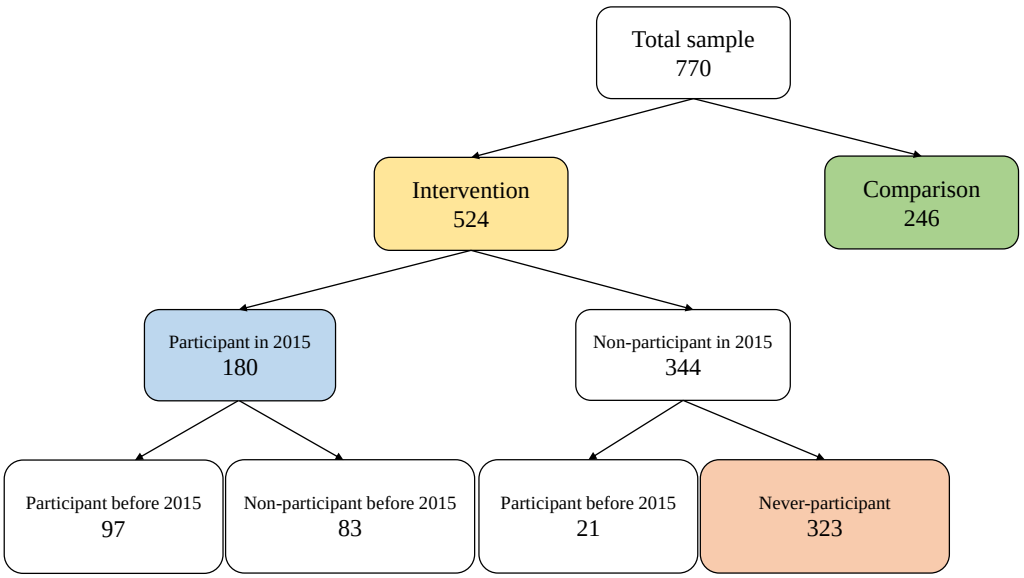


TABLE 5 – Participation au warrantage

Characteristiques	2013	2014	2015
nombre de ménages	60	105	180
taux d'adoption	0.11	0.20	0.34
nombre moyen de sacs de maïs stockés	14.5	11.5	10.4
nombre moyen de sacs de sorgho stockés	2.2	1.3	1.0
nombre moyen de sacs de mil stockés	0.8	0.5	0.3
part moyenne de la récolte déposée (%)	0.28	0.23	0.34
montant du crédit moyen (FCFA*)	106,998	66,492	84,328
taux de warrantage sans crédit	10%		23%
taux de warrantage avec crédit inférieur au max	35%		77%

* FCFA (Franc des colonies françaises d'Afrique)

TABLE 6 – Impact sur les activités agricoles : estimation des ITT

	(1) échantillon moyenne	(2) ITT régression	
résultat	y_1	coef.	err. std
surface cultivée (ha)	8.56	1.82 ***	0.54
surface de coton (ha)	4.16	1.22 *	0.58
surface de maïs (ha)	2.09	0.46 ***	0.14
surface de sorgho (ha)	1.58	0.32	0.22
cheptel (nombre)	5.63	1.57 **	0.71
bovins de trait (nombre)	2.01	-0.3	0.20
volaille (nombre)	14.36	-2.12	3.41
moutons (nombre)	3.8	0.87	0.82
engrais NPK (kg)	811	163.05 **	76.49
récolte de coton (kg)	3,758	721.58 *	379.09
récolte de maïs (kg)	2,947	-11.31	214.64
récolte de sorgho (kg)	1,039	-156.38	208.49

Note : Cette table présente les impacts ITT. La colonne 1 donne la valeur moyenne des variables de résultats (y_1) parmi les ménages traités en 2016. La colomne 2 donne l'ITT à partir d'une régression MCO (moindres carrés ordinaires) incluant les variables de contrôle mesurées en 2013 : surface totale, surface en coton, surface en maïs, surface en sorgho, éducation du chef de ménage (alphabétisé=1), la taille de la famille, le nombre de charrues, la main d'oeuvre familiale, le nombre de têtes de bétail, le nombre de bovins de trait, le nombre de volailles, la quantité d'engrais, l'accès au crédit (oui=1), et l'existence d'un autre magasin de stockage dans le village (oui=1). Les erreurs standard robustes sont ajustées avec les clusters villages. Les symboles ***, ** et * indiquent que le coefficient estimé est statistiquement significatif au seuil de 1%, 5%, et 10% , respectivement

TABLE 7 – Impact sur l'accès à une nourriture suffisante : estimation des ITT

	(1) échantillon moyenne	(2) ITT régression	
résultat	y_1	coef.	err. std
Il reste des céréales en stock aujourd'hui (février), (oui=1)	0.84	0.02	0.047
Il reste suffisamment de céréales jusque la récolte (oui=1)	0.08	0.02	0.063
durée d'autosuffisance (nb de jours)	79	9.84	8.62
quantité de maïs en stock (kg)	477	25.22	166.34
quantité de sorgho en stock (kg)	244	50.16	113.23
quantité de mil en stock (kg)	85	68.68 **	25.82

Note : Cette table présente les impacts ITT. La colonne 1 donne la valeur moyenne des variables de résultats (y_1) parmi les ménages traités en 2016. La colomne 2 donne l'ITT à partir d'une régression MCO incluant les variables de contrôle mesurées en 2013 : surface totale, surface en coton, surface en maïs, surface en sorgho, éducation du chef de ménage (alphabétisé=1), la taille de la famille, le nombre de charrues, la main d'oeuvre familiale, le nombre de têtes de bétail, le nombre de bovins de trait, le nombre de volailles, la quantité d'engrais, l'accès au crédit (oui=1), et l'existence d'un autre magasin de stockage dans le village (oui=1). Les erreurs standard robustes sont ajustées avec les clusters villages. Les symboles ***, ** et * indiquent que le coefficient estimé est statistiquement significatif au seuil de 1%, 5%, et 10% , respectivement

Après trois années de warrantage, les paysans des villages bénéficiaires cultuvent en moyenne une plus grande surface (+1.8 ha, i.e. 27%), pour le coton et le maïs. Ce résultat est conforté par les entretiens qualitatifs nous indiquant que de nombreux participants utilisent leur crédit pour embaucher des travailleurs journaliers pour la récolte du coton. Le facteur limitant principal de la culture du ton dans le Tuy et le Mouhoun n'est pas la terre disponible mais la trésorerie pour rémunérer la main d'oeuvre salariée au moment de la récolte. Le crédit du warrantage permet d'alléger la contrainte de liquidité en décembre, principale période de réclte du coton.

L'utilisation d'engrais augmente avec le warrantage d'environ 160 kg de NPK (25%) en moyenne par ménage des villages bénéficiaires. Ce résultat est logique puisque d'une part l'utilisation d'engrais est en partie liée au coton (via la distributuion d'engrais à crédit par la société cotonière) et d'autre part le déstockage des céréales en warrantage intervient vers mai, ce qui déserre la contrainte de liquidité au moment des achats d'engrais du maïs.

Le bétail augmente en moyenne de 1,5 tête de bétail (+38%). Là encore, il sagit d'un résultat attendu puisque le fait de repousser dans le temps la mise à disposition des céréales repousse la nécessité de déstocker le capital animal pendant la soudure, et donc réduite la décapitatlisation en soudure.

On étudie ensuite les impacts pour les ménages participants, y compris pour les varaibles que nous n'avons pu mesurer que ex post. On doit alors utiliser des estimateurs adaptés à la correction des biais de sélection des participants. L'impact ATT a été estimé de trois façons, (i) par appariement des différences de différences en ce qui concerne les variables agricoles, (ii) par appariement des simples différences en ce qui concerne les variables de sécurité alimentaire, (iii) par variable

instrumentale pour les variables agricoles et les variables de sécurité alimentaire (l'instrument étant une dichotomique de traitement du village).

Les résultats montrent que l'adoption du warrantage a augmenté les trois années pour atteindre 30% des ménages des villages traités, qui stockent en moyenne 30% de leur récolte en warrantage. Des informations informelles de notre partenaire la CPF (Confédération Paysanne du Faso) indiquent de que cette dynamique s'est poursuivie depuis. Un des villages a construit un deuxième entrepôt à ses frais depuis.

En moyenne, les ménages participants accroissent leur surface cultivée de 2 ha par rapport aux témoins, principalement en coton (+1,5 ha) et en maïs (0,5 ha), ils accroissent leur capital animal (+2 boeufs), ils utilisent plus d'engrais (+230 kg).

TABLE 8 – Impact sur les activités agricoles des participants estimé par différences de différences

	(1) valeur moyenne	(2) 2 plus proches voisins matching			(3) ipwr ajustement			(4) OLS regression			(5) IV regression		
variable dépendante	y_1	coef.		s.e.	coef.		s.e.	coef.		s.e.	coef.		s.e.
surface totale (ha)	10.71	1.51	**	*0.68*	1.00	*	*0.54*	1.36	**	*0.64*	2.41	**	*1.04*
surface coton (ha)	5.57	1.45	***	*0.47*	1.17	***	*0.35*	1.29	**	*0.51*	1.70	***	*0.62*
surface maïs (ha)	2.41	0.35	*	*0.21*	0.28	**	*0.14*	0.28	*	*0.14*	0.65	**	*0.33*
surface sorgho (ha)	1.78	-0.12		*0.22*	-0.07		*0.22*	0.06		*0.26*	0.82	*	*0.44*
cheptel (nb têtes)	6.33	1.43	◇	*0.91*	1.39	**	*0.65*	1.54	**	*0.66*	2.71	*	*1.42*
bovins de tractions (nb têtes)	2.53	0.07		*0.21*	0.07		*0.17*	0.09		*0.21*	-0.39		*0.32*
volaille (nb)	18.43	2.28		*2.78*	0.05		*2.22*	0.70		*3.04*	-3.96		*4.78*
moutons (nb)	4.50	0.44		*0.52*	1.18	**	*0.50*	1.15	**	0.48	1.36		*1.05*
engrais utilisé (kg)	1125.28	192.99	**	*76.33*	189.14	***	*58.88*	202.09	**	*77.67*	230.04	**	*117.20*
coton récolté (kg)	5321.49	827.95	*	*430.22*	754.25	**	*336.20*	913.68	◇	*548.41*	781.65		*664.56*
maïs récolté (kg)	3732.01	474.32	◇	*324.81*	476.93	*	*252.65*	529.51		*328.86*	321.95		*607.30*
sorgho récolté (kg)	1219.51	-153.51		*178.10*	-132.00		*158.74*	-142.85		*296.42*	-177.05		*330.77*

Note : la colonne 1 donne la valeur moyenne de l'outcome parmi les ménages traités en 2016. La colomne 2 donne l'ATT en utilisant la différence de différences des 2 plus proches voisins, avec l'estimateur aux écarts types robustes selon Abadie and Imbens (2006, 2016). La colonne 3 donne l'ATT en utilisant la régression ipwra (inverse-probability-weighted regression adjustment). La colonne 4 donne l'ATT avec OLS sur les différences de différences avec des écarts types robustes et clusterisés au niveau village. La colonne 5 donne l'ATT par différence de différence avec comme variable instrumentale de la participation la variable indicatrice de localisation aléatoire des entrepôts dans leur village ou non. Les notations ***, **, * et ◇ indiquent que les coefficients estimés sont statistiquement différent de zéro aux seuils de 1%, 5%, 10% et 15% , respectivement.

Concernant leur soudure, la disponibilité de céréales augmente (13% de points de pourcentages), la durée d'autosuffisance augmente de 17 jours, la quantité de maïs en stock en fin de soudure augmente de 200 kg. Ils consomment régulièrement plus de poisson, d'huile et de fruits.

TABLE 9 – Impact sur la disponibilté alimentaire des participants

	(1) sample mean	(2) 2-nearest-neighbor matching			(3) ipwr adjustment			(4) OLS			(5) IV		
variable dépendante	y_1	coef.		s.e.	coef.		s.e.	coef.		s.e.	coef.		s.e.
Dummy céréales en stock (oui=1)	0.94	0.09	**	*0.04*	0.06	**	*0.03*	0.05		*(a)*	0.01		*(a)*
Dummy céréales suffisantes pour éviter la soudure (yes=1)	0.81	0.13	***	*0.05*	0.07	*	*0.04*	0.06		*(a)*	0.03		*(a)*
durée de l'auto-suffisance (jours)	95.4	17.4	***	*6.6*	17.7	***	*5.6*	17.1	*	*8.5*	21.3	*	*11.5*
quantité de maïs en stock (kg)	746.0	213.2	**	*101.5*	197.6	*	*104.1*	216.5		*178.0*	58.1		*213.8*
quantité de sorgho en stock (kg)	318.8	-167.7		*209.8*	-98.6		*125.2*	-71.6		*205.3*	-68.9		*152.8*
quantité de mil en stock (kg)	94.81	34.2		*51.9*	42.1		*49.1*	33.6		*47.6*	130.8		*79.7*

Note : la colonne 1 done la valeur moyenne de l'outcome parmi les ménages traités en 2016. La colomne 2 donne l'ATT en utilisant la différence de différences des 2 plus proches voisins, avec l'estimateur aux écarts types robustes selon Abadie and Imbens (2006, 2011, 2012). La colonne 3 donne l'ATT en utilisant la régression ipwra (inverse-probability-weighted regression adjustment). La colonne 4 donne l'ATT avec OLS sur les différences de différences avec des écarts types robustes et clusterisés au niveau village. La colonne 5 donne l'ATT par différence de différence avec comme variable instrumentale de la participation la variable indicatrice de localisation aléatoire des entrepôts dans leur village ou non. Les notations ***, **, * et ⋄ indiquent que les coefficients estimés sont statistiquement différent de zéro aux seuils de 1%, 5%, 10% et 15% , respectivement.

TABLE 10 – Impact sur les groupes alimentaires consommés

groupes alimentaires consommés	(1) moyenne	(2) 2-nn			(3) ipwr			(4) probit		(5) IV	
Plusieurs fois par semaine (oui= 1)	y_1	coef.		s.e.	coef.		s.e.	coef.		coef.	
légumineuses	0.05	-0.04		*0.03*	-0.03		*0.02*	-0.03		-0.01	
oléagineux	0.20	0.01		*0.05*	0.04		*0.04*	0.03		-0.04	
viande	0.20	0.03		*0.04*	-0.01		*0.04*	-0.01		-0.11	
poisson	0.66	0.13	**	*0.06*	0.15	***	*0.05*	0.14	*	0.20	*
produits laitiers	0.07	-0.01		*0.03*	0.00		*0.02*	0.00		0.03	
oeufs	0.05	0.03		*0.02*	0.03		*0.02*	0.02		0.09	**
huile	0.88	0.09	**	*0.04*	0.10	***	*0.04*	0.08		0.12	*
légumes	0.25	-0.05			-0.04		*0.04*	-0.02		-0.11	
fruits	0.05	0.03	*	*0.00*	0.04	**	*0.02*	0.04	**	0.16	***
sucres	0.85	-0.01		*0.02*	-0.04		*0.03*	-0.04		-0.13	
sauce et condiments	0.99	0.03		*0.02*	0.02		*0.14*	0.02	*	0.02	
Quotidiennement (oui= 1)											
légumineuses	0.01	0.00		*0.01*	0.00		*0.01*	0.00		0.03	
oléagineux	0.06	-0.04		*0.04*	-0.01		*0.02*	-0.01		-0.04	
viande	0.03	0.02		*0.02*	0.00		*0.02*	0.00		-0.02	
poisson	0.38	0.08	◇	*0.06*	0.10	**	*0.05*	0.08		0.04	
produits laitiers	0.04	0.00		*0.03*	0.00		*0.02*	0.00		0.01	
oeufs	0.01	0.01		*0.01*	0.01		*0.01*	0.00		0.00	
huiles	0.68	0.07		*0.06*	0.08	*	*0.05*	0.06		0.08	
légumes	0.18	-0.03		*0.05*	0.01		*0.04*	0.02		-0.05	
fruits	0.03	0.02	◇	*0.02*	0.03	**	*0.01*	0.03	*	0.03	◇
sucres	0.73	-0.03		*0.05*	-0.05		*0.04*	-0.04		-0.13	◇
sauce et condiments	0.98	0.09	***	*0.03*	0.09	***	*0.03*	0.08	*	0.11	***

Note : la colonne 1 donne la moyenne de l'outcome parmi les ménages traités en 2016. La colonne 2 donne l' ATT en utilisant l'estimateur des 2 plus proches voisins (2-nn). La colonne 3 donne l'ATT avec l'estimateur ipwra. La colonne 4 donne l'ATT avec une régression. La colonne 5 donne l'ATT avec une régression sur variable instrumentale. (a) Pour les variables dépendantes binaires, les colonnes 4 et 5 donne l'impact marginal calculé à partir d'un modèle probit (pas d'écarts types fournis). Les ***, **, * et ◇ indiquent que les coefficients estimés sont statistiqueme,t significatifs aux seuols de 1%, 5%, 10% and 15% , respectivement.

Les raisons de cette efficacité du warrantage ont été développées précédemment. L'une a trait à l'engagement contraignant vis-à-vis de soi-même que permet le warrantage et qui diffère dans le temps l'épuisement des ressources stockées.

Conclusion sur le biais pour le présent

Mes travaux alimentent l'idée que l'agriculture au Burkina Faso fait face à une exploitation accélérée des ressources propres, par rapport à ce que souhaiteraient les ménages, conduisant à la soudure. De même que l'absence de coordination entre différents exploitants d'une ressource commune aboutit à une tragédie des communs, la discordance entre les choix d'un agent à différentes périodes du temps aboutit à une surexploitation de ses ressources par lui-même. Il existe un grand nombre d'exemples de tragédie des ressources propres, le surendettement, le fait de toujours remettre au lendemain un effort, les addictions aux jeux ou aux substances toxiques, etc. En réalité, à chaque fois qu'on est moins vertueux que prévu par nous même, dans un sens égoïste du terme, on tombe dans une tragédie des ressources propres, plus ou moins dommageable.

Le mécanisme qui permet de résoudre cette tragédie (et d'accroître l'utilité intertemporelle) consiste à donner à l'agent en première période la possibilité de contraindre ses choix de seconde période. Il s'agit d'une forme de coordination entre le soi présent et le soi lointain en défaveur du soi intermédiaire qui ne sera pas aussi économe que prévu. L'amélioration permise par ce mécanisme augmente l'utilité intertemporelle, mais ce n'est pas une amélioration au sens de Pareto car l'utilité de seconde période est inférieure après cette amélioration. C'est là une différence avec la coordination permettant de résoudre une tragédie des communs qui est en théorie une amélioration au sens de Pareto (sans perdant). Dans le cas du warrantage, il s'agit plutôt d'une amélioration redistributive au profit du futur (même si à long terme, l'accroissement de la production et du capital animal pourraient théoriquement aussi profiter au joueur intermédiaire et le warrantage deviendrait alors une amélioration de Pareto).

4 Erreurs d'anticipation et volatilité atypique

La litérature sur la volatilité des prix donne des clés pour comprendre comment réduire la volatilité (le stockage spéculatif (Williams and Wright, 1991; Cafiero et al., 2011; Wright, 2011), le stockage public dans certaines conditions (Barrett, 1997; Nyange and Wobst, 2005; Jayne et al., 2008), l'intégration des marchés), comment modéliser la volatilité à partir de séries de prix (Bobenrieth et al., 2013; Serra and Gil, 2013; Gilbert and Morgan, 2010) ou de simulation (Frechette, 1999; Deaton and Laroque, 1992), mais elle n'explique pas bien ce qui crée la volatilité, en dehors des chocs de production et des cas de spéculateurs monopoleurs.

Ici, on étudie le cas de la volatilité produite localement ou accrue localement, par des erreurs d'anticipation qui engendrent des erreurs de gestion des stocks.

4.1 Erreurs d'anticipation de prix, contraintes de liquidité et volatilité atypique

Nous montrons que les aspects atypiques de la volatilité des prix du maïs au Burkina Faso (skewness négative) sont expliqués par les comportements des producteurs sous contrainte de liquidité (Maître d'Hôtel and Le Cotty, 2018).

Les principales études des propriétés de la volatilité des prix constatent que les chutes de prix sont plus modérées que les pics de prix, ce qui donne aux distributions de prix une loi non pas normale, mais avec une skewness positive (distribution déformée avec une queue de distribution plus étalée à droite). Cette propriété est très générale et concerne toutes les céréales mais aussi la plupart des produits agricoles. La théorie du stockage compétitif explique cela par le fait que les chutes de prix engendrent des achats spéculatifs sans limite qui enrayent ces chutes de prix, alors que les hausses de prix engendrent des ventes qui enrayent ces hausses de prix, mais uniquement dans la limite des stocks existants (Deaton and Laroque, 1992). Cette asymétrie entre les ventes limitées et les achats illimités entraine une asymétrie de la distribution des prix, avec des pics de prix plus marqués que les chutes de prix. Tout ceci s'explique très bien dans le cadre des anticipations rationnelles, qui suppose notamment l'absence d'erreur d'anticipations.

Mais l'observation des prix du maïs au Burkina Faso montre une distribution qui non seulement n'a pas cette skewness positive, mais a parfois une skewness négative, c'est-à-dire que les chutes de prix sont plus marquées que les pics de prix (Table11).

TABLE 11 – caractéristiques moyennes de la distribution des prix de marché du maïs (données mensuelles SONAGESS (Société nationale de gestion des stocks de sécurité alimentaire du Burkina Faso) , 33 marchés, 2004-2013)

	obs par marché	prix moyen	écart type moyen	skewness moyenne	kurtosis moyenne	marchés avec skewness négative	marchés avec kurtosis négative
série complète	121	134,87	31,39	0,25	-0,21	3	15
saison avant récolte	52	140,52	36,36	0,33	-0,40	4	27
saison après récolte	69	130,58	26,32	0,11	0,17	15	14

Ce tableau et l'observation des séries de prix nous conduisent à l'hypothèse que cette propriété est surtout dûe aux chutes de prix après la récolte (Figure 8). La définition d'une chute de prix inattendue est donnée par un modèle économétrique de comportement de prix (ARCH pour autoregressive conditional heteroscedasticity) qui donne le prix prévu en tenant compte de la saisonalité moyenne et compare le prix réel au prix prévu.

Pour expliquer ces comportements de prix, on construit un modèle de stockage compétitif proche de Deaton et Laroque, en y ajoutant avec une contrainte de liquidité qui empêche les producteurs stockeurs d'acheter le maïs à la récolte en cas de chute de prix. Les producteurs qui sont supposés acheter du maïs quand les prix baissent dans le modèle de stockage spéculatif de Deaton et Laroque ne peuvent le faire dans notre modèle, faute de liquidité et donc la chute des prix n'est pas enrayée comme dans le modèle standard.

Dans le modèle standard, les décisions de stockage compétitif dépendent uniquement du profit

FIGURE 7 – chutes de prix inattendues et de pics de prix inattendus pendant une année au Burkina Faso, données mensuelles SONAGESS , 33 marchés, 2004-2013

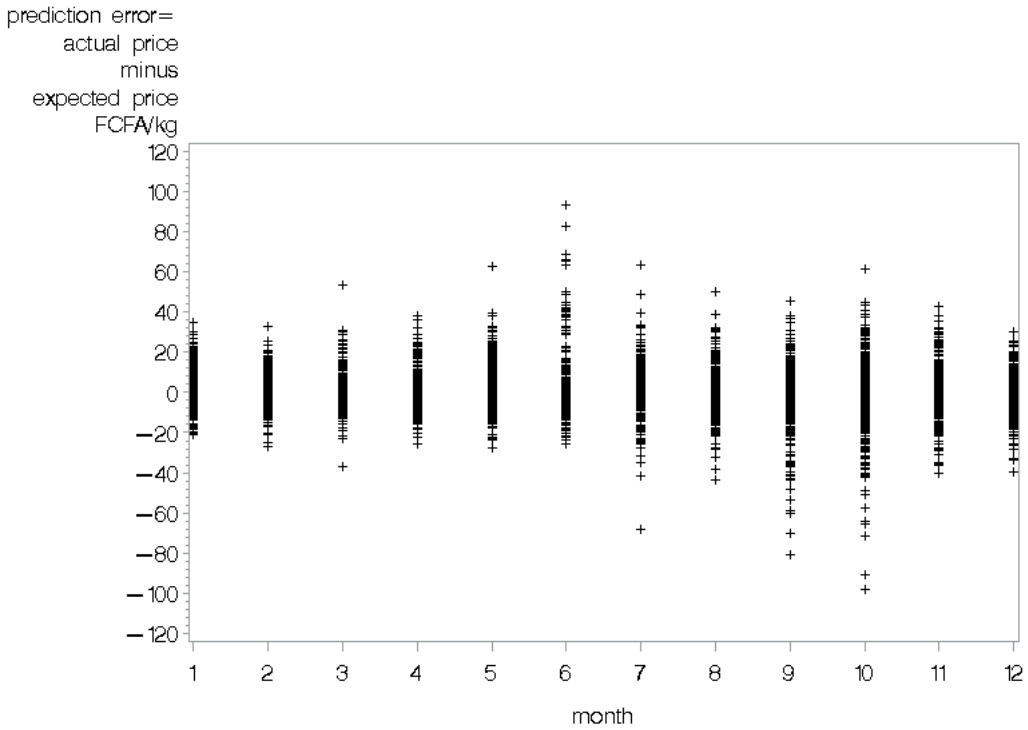
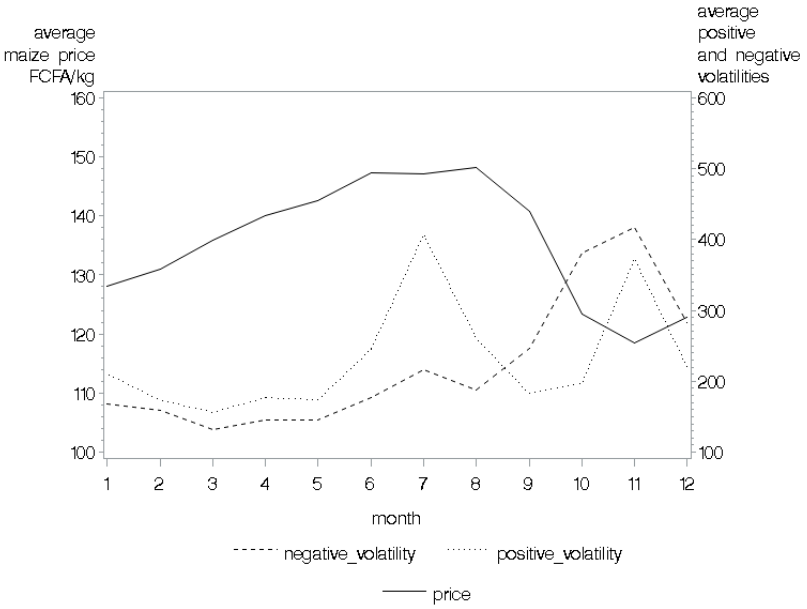


FIGURE 8 – moyennes mensuelles de chutes de prix inattendues et de pics de prix inattendus pendant une année au Burkina Faso, données mensuelles SONAGESS , 33 marchés, 2004-2013



espéré que le stockeur réalise en conservant son stock I_t entre t et $t+1$, plutôt que le vendre. Ce profit espéré s'écrit :

$$[\beta(1-\delta)E_t p_{t+1} - p_t]\, I_t \quad ; \quad I_t \geq 0 \tag{6}$$

où β is the taux d'actualisation, δ est le taux de dépréciation du stock, p_t est le prix à la période t, and E_t est l'espérance conditionnelle à l'information diponible à t, qui est le volume de stock existant. Ce volume de stock disponible à la période t est égal au stock conservé de la période précédente $(1-\delta)I_{t-1}$ plus éventuellement la nouvelle récolte z_t. La vériable z_t vaut zéro toute l'année, sauf au moment de la récolte.

L'équation clé que nous introduisons pout intégrer la contrainte de liquidité est que le stock ne peut augmenter par achat de céréales (il augmente uniquement à la récolte)

$$I_t \leq (1-\delta)I_{t-1} + z_t \tag{7}$$

Les conditions du premier ordre de la maximisation de (19) sous contrainte de liquidité sont :

$$\text{si} \quad E_t p_{t+1} < \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad \text{alors} \quad I_t = 0 \tag{8}$$

$$\text{si} \quad E_t p_{t+1} = \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad \text{alors} \quad 0 < I_t < (1-\delta)I_{t-1} + z_t \tag{9}$$

$$\text{si} \quad E_t p_{t+1} > \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad \text{alors} \quad I_t = (1-\delta)I_{t-1} + z_t > 0 \tag{10}$$

La dernière équation reflète la contrainte de liquidité et est responsable des chutes de prix supplémentaires par rapport au modèle standard. Ce n'est pas parce que le producteur anticipe une hausse de prix qu'il peut acheter des céréales jusqu'à rétablir un équilibre de prix $E_t p_{t+1} = \frac{p_t}{\beta(1-\delta)} - p_{t+1}$.

Par ailleurs, l'analyse des séries de prix sur 33 marchés agricoles au Burkina Faso fait apparaître des comportements difficilement compatibles avec l'hypothèse d'absence d'erreur d'anticipation du cadre théorique des anticipations rationnelles. En particulier, alors que les prix chutent tous les ans à la récolte, cela devrait engendrer des ventes totales des stocks en fin de soudure dans la rationalité spéculative de Deaton et Laroque, ce n'est pas toujours ce qu'il se passe. Certains producteurs conservent des stocks de report après la récolte. Ceci peut s'expliquer par de la précaution, mais aussi par des erreurs d'anticipations. Si la chute de prix arrive un peu plus tôt que prévu par exemple en août, il est alors trop tard pour vendre, ce qui entraîne un stock de report, et comme les achats sont plus limités que dans le modèle original, les chutes de prix qui suivent sont plus fortes que prévu. C'est ce que nous intégrons dans notre modèle de stockage compétitif.

L'erreur d'anticipation étant simplement définie comme $\eta_{t,t+1} = E_t p_{t+1} - p_{t+1}$, on montre qu'une condition suffisante pour que l'erreur d'anticipation conduise à un excès de stock en $t+1$ est $\begin{cases} 0 \leq \frac{p_t}{\beta(1-\delta)} - p_{t+1} < \eta_{t,t+1} \\ p_{t+1} < \beta(1-\delta)E_{t+1}p_{t+2} \end{cases}$

Il suffit que (i) le producteur s'attende à une hausse notable du prix (incompatible avec un déstockage en t) alors que la hausse réelle est faible ou négative (compatible avec un déstockage

en t), et (ii) à la période suivante, le producteur continue à anticiper une hausse de prix suffisante (incompatible avec un déstockage en $t+1$).

L'impact de ces erreurs sur le prix d'équilibre de marché est obtenu après étude des conditions d'équilibre offre-demande.

Enfin, nous étudions la contrepartie empirique de ce résultat. La volatilité des prix est estimée à partir d'un modèle ARCH (Autoregressive conditional heteroscedastic model), qui mime le comportement "normal " des prix, et produit la série des écarts à ce comportement normal. Nous récupérons la séries d'écarts de prix positifs et la série des écarts de prix négatifs, comme des mesures des pics de prix non anticipés par les agents et les chutes de prix non anticipées par les agents.

On apparie alors la série de prix et d'erreurs d'anticipation ainsi construite aux données de stocks de report issues de l'enquête permanente agricole du Burkina Faso consuite par le minsitère de l'agriculture. L'estimation d'un panel dynamique (avec les valeurs retards des variables endogènes) nous permet alors de mesurer l'effet de ces erreurs d'anticipations estimées sur les excès de stocks, et on montre que les chutes de prix non anticipées avant la récolte ont un effet sur les stocks de report invendus à la prochaine récolte (Table 12). Ces stocks de report accentuent la volatilité négative des prix après la récolte (Table 13).

TABLE 12 – Effet des chutes de prix non anticipées pendant la soudure sur les stocks de report en fin de soudure

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
stock de report année précédente	0.19 ***	0.42***	0.15 ***	0.19	0.10 ***	0.09	0.10	0.26
chutes de prix non anticipées	0.28**	0.38	0.57	1.13**	0.33	0.96**	1.33 *	-0.02
récolte	0.13***	0.06 *	0.22*	0.06**	0.10**	0.19***	0.23***	0.06
Constante	-36.68	-60.43	-214.66	113.88*	123.39	-192.05*	-279.28	10.85
Obs	264	264	264	264	264	264	264	264
période utilisée pour les chutes de prix	Nov-Oct	Juil	Juil-Aout	Juil-Sept	Aout	Aout-Sept	Sept	Oct

TABLE 13 – Effet des stocks de report avant récolte sur les chutes de prix post-récolte

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
chutes de prix non anticipées (t-1)	0.13	-0.12	-0.14 **	-0.10 **	-0.09 *	0.00	0.07
stock de report	0.02 **	0.09	0.12 ***	0.13 *	0.11 **	0.11 **	0.06 *
récolte	-0.03 *	0.01	-0.12 **	-0.07 **	-0.05	-0.04	-0.03
Constanet	235.38 ***	273.63	588.70 ***	430.85***	368.17***	304.92 ***	269.24***
Obs	264	264	264	264	264	264	264
période de chutes de prix	Nov-Oct	Nov	Nov-Dec	Nov-Jan	Nov-Fev	Nov-Mars	Nov-Avr

TABLE 14 – Effet des stocks de report avant récolte sur les chutes de prix post-récolte, suite.

	[8]	[9]	[10]	[11]	[12]	[13]
chutes de prix non anticipées (t-1)	-0.24	0.01	0.02	0.11	-0.14	-0.25
stock de report	0.03	0.15	0.03	-0.28	0.01	0.16
récolte	-0.16**	-0.12	-0.01	0.02	0.01	0.00
Constante	579.20***	362.98**	240.88 ***	142.98 ***	186.92 ***	223.69***
Obs	264	264	264	264	264	264
période de chutes de prix	Dec	Dec-Jan	Dec-Fev	Jan	Jan-Fev	Fev

4.2 Coûts de transport et volatilité locale

Ce travail est le fruit de la thèse de Moctar Ndiaye à Supagro-Montpellier que j'ai co-encadrée. Moctar a notamment réalisé les estimations économétriques de cet article. Nous montrons dans cet article que lorsque la volatilité des prix est produite localement dans un village, par des chocs d'achat ou de vente, elle est d'autant plus forte que l'éloignement économique de ce village est élevé (Le Cotty et al., 2017).

La littérature sur les coûts de transport et la volatilité des prix a étudié comment les shocks de prix se transmettent d'un marché à l'autre en fonction du coût de transport (Badiane and Shively, 1998; Abdulai, 2000). Mais la question que nous posons est un peu différente : Comment un choc local est il absorbé localement en fonction du coût de transport avec un marché central ?

Pour cela nous construisons un modèle d'échange fondé sur un modèle standard de commerce international avec coût de transport (Samuelson, 1952) auquel nous imposons un choc de quantité aléatoire. Cela peut se produire si une route est coupée par les inondations et crée brutalement un excès d'offre ou un déficit d'offre local, un commerçant arrive dans le vilage et achète massivement, l'Etat place des vivres à prix subventionné, etc.

Il existe deux régimes de prix possibles selon que 2 unités échangent ou pas. Soit E la quantité échangée entre un village et un centre urbain, P^u le prix dans le centre urbain et P^r le prix dans le village rural, T est le coût de transport, $V(T)$ est le coût de transaction variable et F est le coût de transaction fixe. Le centre urbain achète au village si et seulement si le prix rural est inférieur au prix urbain après paiement du transport et des coûts de transaction. Le centre urbain achète au village jusqu'à ce que les prix s'équilibrent. Les deux régimes de prix s'écrivent donc

$$\begin{aligned} P^u &= P^r + T + V(T) + F \quad if \quad E > 0 \\ P^u &< P^r + T + V(T) + F \quad if \quad E = 0 \end{aligned} \tag{11}$$

Le village rural a une fonction d'offre qui dépend de ce prix, du stock villageois disponible S_t, et d'un aléa θ_t

$$x_t(P_t^r, S_t, t, \theta_t) \tag{12}$$

En ignorant la possibilité de stock de report, le stock disponible est égal à la dernière récolte H moins la somme des ventes depuis la dernière récolte, indexée $t = 0$.

$$S_t = H - \sum_{i=0}^{t} x_i \tag{13}$$

En utilisant (12) pour expliciter (13), on obtient une expression de S_t sans les x_i, $S_t(H, P_0^r, ..., P_t^r, t, \theta_0, ..., \theta_t)$. On peut alors expliciter l'offre en fonction des prix passés et des aléas passés :

$$x_t(H, P_0^r, P_1^r, ..., P_t^r, t, \theta_0, \theta_1, ..., \theta_t) \tag{14}$$

L'équilibre offre- demande $m_t(P_t^u)$, en utilisant les conditions ci-dessus donne

$$T = P_t^u - P_t^r - V(T) - F \quad ; \quad x_t(H, P_0^r, P_1^r, ..., P_t^r, t, \theta_0, \theta_1, ..., \theta_t) = m_t(P_t^r + T + V(T) + F) \tag{15}$$

$$T > P_t^u - P_t^r - V(T) - F \quad ; \quad x_t = 0 \tag{16}$$

On compare la statique comparative des deux régimes en différenciant totalement les équations (15) et (16), et on montre que les chocs de prix sont plus importants en magnitude dans le régime déconnecté, à aléa identique.

Nous estimons ensuite le comportement des prix du maïs au Burkina Faso par modèle auto-régressif avec hétéroscedasticité conditionnelle en utilisant le coût de transport comme variable explicative des deux équations (équation du prix et équation de variance conditionnelle du prix). Différentes mesures du coût de transport, la plus convaincante de notre point de vue étant le temps de trajet) confirment la conclusion que le coût de transport accroît la volatilité rurale.

L'une des spécifications ARCH proposée est la suivante :

$$\begin{aligned} P_{it} = \gamma_0 + \gamma_1 P_{it-1} + \gamma_2 IP_t + \gamma_3 ER_t + \gamma_4 HARVEST_t + \gamma_5 LEAN_t + \gamma_6 BORDER_i \\ + \gamma_7 TRANSPORT_i + \gamma_8 TREND_t + \gamma_9 RAINFALL_i + \sum_1^3 \eta_k REGION_k \\ + \sum_1^9 \sigma_k ETHNY_k + \sum_{j=1}^{27} \Delta_j M_j + \varepsilon_{it} \qquad \varepsilon_{it} \sim \mathcal{N}(0, h_{it}) \end{aligned} \tag{17}$$

$$\begin{aligned} h_{it} = \varphi_0 + \varphi_1 \varepsilon_{it-1}^2 + \varphi_2 P_{it-1} + \varphi_3 IP_t + \varphi_4 ER_t + \varphi_5 HARVEST_t + \varphi_6 LEAN_t + \varphi_7 BORDER_i \\ + \varphi_8 TRANSPORT_i + \varphi_9 TREND_t + \varphi_{10} RAINFALL_t + \sum_1^3 \chi_k REGION_k + \\ \sum_1^9 \phi_k ETHNY_k + \sum_{j=1}^{27} \rho_j M_j + \nu_{it} \qquad \nu_{it} \sim \mathcal{N}(0, \sigma) \end{aligned} \tag{18}$$

où P_{it} est le prix du marché i obseré le mois t, IP_t est le prix international au mois t, ER_t est le taux de change national au mois t, $HARVEST_t$ est une dichotomique de la saison de récolte,

$LEAN_t$ est une dichotomique de la saison de soudure, $BORDER_i$ est la distance à la frontière, $TRANSPORT_i$ est le coût de transport (approximé par le temps de transport), $TREND_t$ est la tendance, $RAINFALL_i$ est la pluviométrie annuelle de la province du marché i, $REGION_k$ est une dichotomique régionale,$ETHNY_k$ est une dichotomique de l'ethnie dominante k, M_j est une variable dichotomique qui vaut 1 si le marché est situé dans une zone de production du maïs, et ε_{it} est le terme d'erreur hétéroscedastique de la première équation, de variance h_{it}, et ν_{it} est le term d'erreur homoscédastique de la seconde équation.

Le résultat d'estimation est

TABLE 15 – Effet du coût de transport sur la volatilité du prix du maïs

	[1]		[2]		[3]		[4]		[5]		[6]		[7]	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	33.88***	12.09	30.80*	-81.49***	35.67***	-84.34*	34.19***	174.17***	45.55***	209.19***	33.41***	-100.95**	33.22***	49.16
	(0.000)	(0.783)	(0.000)	(0.075)	(0.000)	(0.060)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.213)
Arch term		0.15***		0.15***		0.16***		0.21***		0.24***		0.16***		0.14***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Lagged price	0.88***	1.15***	0.87***	0.51***	0.87***	0.57***	0.85***	0.47***	0.83***	0.29***	0.92***	1.54***	0.91***	1.54***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
International price	0.05***	-0.75***	0.06***	-0.55***	0.06***	-0.58***	0.06***	-0.31***	0.05**	-0.19**	0.04***	-0.61	0.04***	-0.61***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.144)	(0.000)	(0.000)
Exchange rate	-0.03***	0.15*	-0.03***	0.50***	-0.04***	0.51***	-0.03***	-0.07	-0.03***	-0.04	-0.03***	0.11***	-0.03***	-0.02
	(0.000)	(0.087)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.352)	(0.000)	(0.423)	(0.000)	(0.000)	(0.000)	(0.739)
Harvest dummy	-6.37***	132.71***	-6.76***	140.99***	-6.75***	142.60***	-6.51***	113.72***	-6.59***	76.46***	-5.95***	126.20***	-6.09***	118.25***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	1.92***	0.03*	1.90***	-2.59	1.97***	-2.38	1.40***	-2.90	1.57***	-4.39*	1.18***	-1.50	1.00***	-0.56
	(0.000)	(0.992)	(0.000)	(0.439)	(0.000)	(0.517	(0.000)	(0.129)	(0.000)	(0.076)	(0.004)	(0.586)	(0.009)	(0.827)
Time to the border	0.01***	-0.16***	0.04***	-0.00	0.01**	0.04**	0.01***	0.12***	0.04***	0.03	0.01*	-0.17***	0.01	-0.42***
	(0.005)	(0.000)	(0.000)	(0.910)	(0.000)	(0.013)	(0.004)	(0.002)	(0.000)	(0.656)	(0.054)	(0.000)	(0.314)	(0.000)
Time to Ouaga	-0.01***	0.21***					-0.01***	0.09***	-0.01***	0.11***	-0.01***	0.25***	-0.01**	0.38***
	(0.000)	(0.000)					(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.000)	(0.029)	(0.000)
Distance to Ouaga			-0.03***	0.18***										
			(0.000)	(0.000)									)	
Unpaved road					-6.35***	16.86***								
					(0.000)	(0.000)								
Trend	-0.06***	-1.05***	-0.06***	-1.33***	-0.06***	-1.29***	-0.05***	-1.45***	-0.05***	-1.54***	-0.05***	-1.04***	-0.05***	-1.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	NO	YES	NO	YES	NO	YES	YES	YES	YES	NO	NO	NO	NO
Annual rainfall									-0.01***	-0.01				
									(0.005)	(0.575)				
South Sahelian climate											-2.16**	43.18***		
											(0.013)	(0.000)		
North soudanian climate											-2.88***	73.41***		
											(0.001)	(0.000)		
South soudanian climate											-2.50**	28.19**		
											(0.015)	(0.005)		
Peulh ethny													2.90**	-33.19***
													(0.011)	(0.003)
Gourmantche ethny													0.65	60.05***
													(0.656)	(0.000)
Bissa ethny													-0.55	-33.20***
													(0.686)	(0.008)
Lobi ethny													2.94*	-22.74
													(0.066)	(0.140)
Senoufo ethny													-0.83	-86.91***
													(0.650)	(0.000)
Dagara ethny													-1.63	-31.50***
													(0.130)	(0.001)
Bobo ethny													-1.14	-6.78
													(0.358)	(0.480)
Gourounsi ethny													-1.03	0.94
													(0.415)	(0.932)
Mossi ethny													-0.27	11.27
													(0.803)	(0.254)
N	3472		3472		3472		3472		3472		3472		3472	
R squared	0.8362		0.8370		0.8371		0.8370		0.8377		0.8311		0.8327	

p-values in brackets
* significant at 10 percent ** significant at 5 percent *** significant at 1 percent
[1] Travel time to Ouagadougou
[2] Kilometric distance to Ouagadougou
[3] Road pavement
[4] Market dummies
[5] Rainfall and market dummies
[6] Climatic zone dummies
[7] Ethnic group dummies

L'effet du coût de transport (time to Ouaga ou Distance to Ouaga) est positif sur la variance (et généralement négatif sur le niveau de prix dans le village), ce qui confirme la théorie développée plus haut.

5 Recherches en cours et futures : Climat, pression sociale et politiques de développement

Mes travaux passés mettent l'accent sur les raisons comportementales du faible investissement dans la production et du déstockage rapide des récoltes. J'inteprète l'insécurité alimentaire saisonnière comme la résultante de choix individuels, dans un contexte agronomique considéré comme donné. Cela a des implications dans la réflexion sur les politiques à mettre en œuvre pour favoriser la sécurité alimentaire.

En l'absence de cette analyse, les problèmes de sous développement agricole en Afrique sont souvent posés comme des contraintes à la production ou à la conservation. Logiquement, les solutions envisagées consistent souvent à lever les contraintes techniques ou à lever les contraintes économiques. Mais bien souvent, la mise à disposition de fonds ou de technologies productives auprès des ménages agricoles, même lorsqu'elle conduit à lever ces contraintes, ne se traduit pas par des modifications durables des investissements ou des technologies utilisées par ces ménages. Mon interprétation est que les gains engendrés par ces investissements ou ces technologies engendrent de la convoitise et augmentent la pression sociale subie par le paysan innovant. L'abandon à la suite d'un projet de développement d'une technologie pourtant saluée pendant la période d'un projet n'est pas un évènement exceptionnel. De manière générale, le développement suppose d'investir, d'entretenir, de sacrifier une part de ressource propre du présent pour une ressource future plus grande mais sujette à pression sociale. La pression sociale sur la production est plus grande que sur la pression sociale sur les facteurs de production parce que la production de chacun est connue de tous, alors que les facteurs de production tels que les dépenses d'engrais, sont ignorés de la plupart des villageois.

Les politiques de développement qui font comme si les paysans avaient simplement envie d'investir pour produire, comme s'ils conservaient le fruit de leur investissement, sont vouées à des difficultés dans le temps parce qu'elles ignorent l'effet de la pression sociale sur l'investissement. A mon avis, il est fondamental que les politiques de développement intègrent le fait que les fruits des efforts des paysans qui investissent ou épargnent puissent être protégés de la pression sociale. Dans cette perspective je compte étudier dans les prochaines années l'efficacité de différentes politiques d'adaptation au changement climatique, en tenant compte de leur capacité à protégrer les bénéficiaires de la pression sociale.

Dans cette section, je présente successivement deux travaux en cours sur des exemples de politiques d'adaptation ou d'atténuation du changement climatique qui ne tiennent pas compte de la pression sociale, et deux projets de recherche futurs dans lesquels je souhaite diriger des doctorants, et où la prise en compte de la pression sociale sera plus explicite dans les politiques d'adaptation.

Mes travaux en cours sur les politiques d'adaptation au changement climatique ou de compensation du changement climatique portent sur (i) l'assurance sécheresse qui est une forme d'investissement par le producteur et qui se heurte au même type de difficultés que celles de l'achat d'engrais traité en première partie (section 6.1) ; (ii) l'assistance alimentaire au Niger qui est également soumise à une forte pression sociale qui réoriente les ressources par rapport aux besoins

identifiés ce qui a des conséquences économiques négatives (section 6.2).

Mes travaux futurs s'intéresseront à l'hypothèse selon laquelle des chocs climatiques engendrent des redistributions de ressources dans les villages, qui engendrent potentiellement des modifications de la pression sociale. J'aimerais dans les années à venir étudier plus en profondeur et grâce à la direction de doctorats l'impact de la pression sociale sur les redistributions intra-groupes et l'investissement (section 6.3) et l'impact du changement climatique sur les changements de pression sociale et les politiques d'adaptation (section 6.4).

5.1 Fréquence des sécheresses et politiques d'assurance climat au Sahel

Ce travail montre par la théorie et par l'économie expérimentale que la demande des paysans pour l'assurance agricole au Burkina Faso diminuer lorsque la fréquence des sécheresses augmente (Leblois et al., 2020).

La question que se pose cet article est la suivante : si le changement climatique se traduit par une plus grande fréquence des sécheresses, est-ce que les impacts de ces sécheresses sur les récoltes seront plus ou moins assurables ? Les recherches sur les assurances climatiques ne portent pas sur la fréquence des risques, qui est considérée comme donnée dans cette littérature, mais sur d'autres raisons de la faible adoption des assurances, comme le risque de base lié à l'imparfaite estimation des dommages. Mais en dehors du risque climatique, il existe des résultats sur l'effet des fréquences des chocs sur la demande d'assurance, et ces résultats se concentrent sur les faibles fréquences. Slovic et al. (1977) montrent que les agents ont une vision déformée du risque lié aux basses fréquences de chocs et s'assurent moins que prévu par l'utilité espérée lorsque la fréquence se réduit (risques rares). A leur suite, plusieurs travaux théoriques et empiriques confirment et donnent une interprétation comportementale à ce phénomène (Kahneman and Tversky, 1979; Kunreuther and Slovic, 1978; Hertwig et al., 2004; Kunreuther et al., 2001). Un nombre plus réduit de travaux similaires trouvent une relation inverse (plus de demande d'assurance contre les risques plus rares), McClelland et al. (1993) and Laury et al. (2009).

Une caractéristique importante de ces différentes expériences est que les auteurs modifient à la fois la fréquence et l'intensité des chocs de façon à garder le dommage moyen identique, et donc la prime d'assurance identique. Ce faisant, ils comparent donc des risques fréquents mais peu intenses et des risques rares mais intenses. Mais il n'est pas non plus absurde de se demander quel effet aurait sur la demande une aggravation du risque, plutôt qu'un changement de nature de risque. Plus précisément, quelle conséquence sur la demande d'assurance aurait un accroissement de la fréquence des chics climatiques pour une même intensité de sécheresse ? Certains pourraient penser au la demande d'assurance contre des risques plus fréquents devrait augmenter, or ce n'est pas le cas. Nous construisons un modèle d'assurance climatique en utilité espérée, donc sans mécanisme de myopie aux risques très rares ou très fréquents, et nous aboutissons au résultat que la demande d'assurance est une courbe en cloche de la fréquence du risque.

La matrice des gains et des probabilités se présente ainsi, avec une probabilité p de sécheresse, et une probabilité r que l'assureur ne paie pas le paysan en cas de sécheresse (r est le risque de base de non remboursement par erreur).

TABLE 16 – Matrice des gains et des probabilités

	indemnité (1-r)	zéro indemnité (r)
pluie (1-p)	0	$1-p$
sécheresse (p)	$(1-r)p$	rp

Le gain espéré par le paysan qui prend une assurance est la différence entre son utilité espéré avec assurance et son utilité espérée sans assurance. Cette différence s'écrit

$$\begin{aligned}\Delta EU = (1-p)u(y-P) + (1-r)pu(y-P) + rpu(y-P-L) \\ - [(1-p)u(y) + pu(y-L)]\end{aligned} \tag{19}$$

Le premier terme est l'utilité espérée sans sécheresse si le paysan prend l'asurance, résultant du bénéfice de la récolte y moins le coût de la prime d'assurance P (ie probabilité de pluie multipliée par l'utilité en cas de pluie). En cas de sécheresse, il y a deux sous-cas : (i) soit le paysan reçoit une indemnité et son utilité reste la même qu'en cas de pluie, $pu(y-P)$, ou le paysan ne reçoit pas d'indemnité et son utilité est plus faible $u(y-P-L)$, L étant la valeur du dommage. L'utilité espérée en cas de sécheresse est la somme pondérée de ces deux sous cas.

On étudie la variation et le signe de cette expression quand p varie, en tenant compte de l'équilibre actuariel $P = mpL(1-r)$ où m est le facteur de charge pour l'assureur (i.e. la part de ce qu'il reçoit du paysan en prime annuelle qu'il lui reverse sous forme d'indemnité, en moyenne).

La solution est une courbe en cloche en fonction de la fréquence des sécheresses, représentée graphiquement ici. Les sécheresses trop fréquentes sont donc moins assurables que les sécheresses moins fréquentes. Quand p augmente, P augmente, et même si la fréquence de l'indemnité augmente, le gain moyen avec assurance devient plus proche du gain sans assurance. Intuitivement, le gain d'un assuré est lié à sa préférence pour la constance des revenus. Cette préférence est d'autant plus grande que son utilité est concave (l'utilité du gain moyen est bien plus grande que la moyenne des utilités d'un gain fort et d'un gain faible). Et lorsque le gain moyen des non assurés devient faible, ce qui est le cas des sécheresses trop fréquentes, le bénéfice dû à la concavité se réduit (l'utilité du gain moyen est de moins en moins au dessus de la moyenne des utilités d'un gain fort et d'un gain faible).

Nous montons une expérience auprès de 200 paysans issus de 10 villages différents et leur proposons différentes situations dans lesquelles varient la fréquence de sécheresse, le facteur de charge et le risque de base.

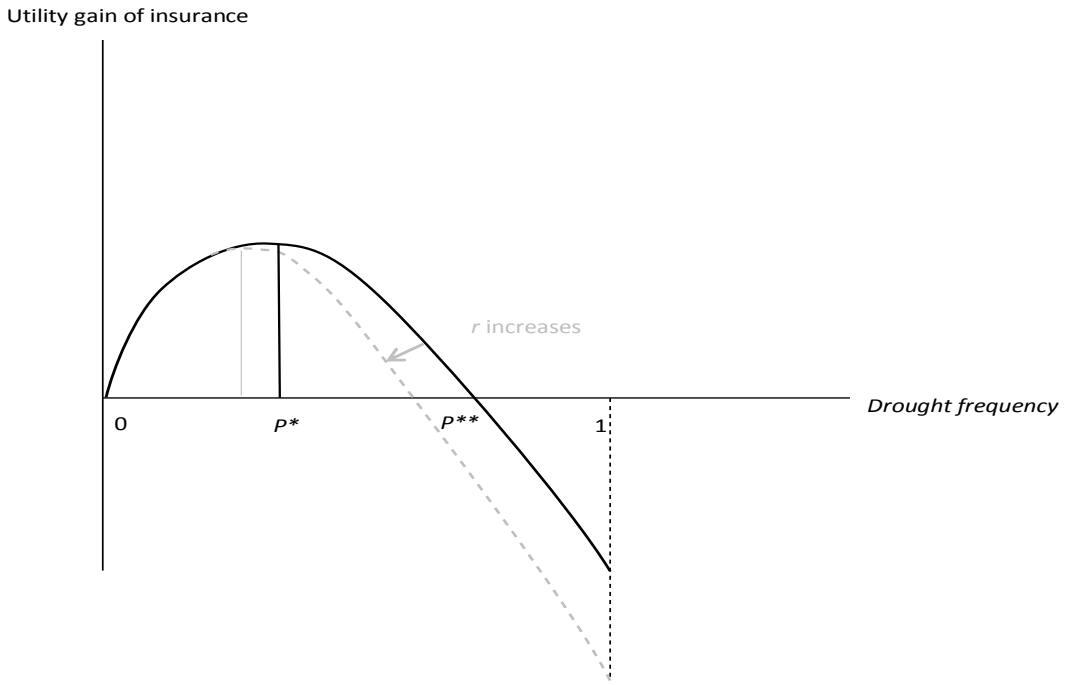


FIGURE 9 – impact théorique de la fréquence des sécheresses sur les gains de l'assurance pour les paysans

.

TABLE 17 – caractéristiques du ciontrat d'assurance et gains espérés des lotteries

jeu (#)	facteur de charge m	risque de base r	fréquence sécheresse p	prime (Fcfa) P	gain(Fcfa) sans assurance pluie $(1-p)$	gain(Fcfa) sans assurance sécheresse p	gain(Fcfa) avec assurance pluie $(1-p)$	gain(Fcfa) avec assurance sécheresse indemn. $(1-r)p$	gain(Fcfa) avec assurance sécheresse pas d'indemn. rp	gains espérés (Fcfa) sans assurance	gains espérés (Fcfa) avec assurance
1	1	0	1/20	40	800	0	760	760	-40	760	760
2	1	0	2/20	80	800	0	720	720	-80	720	720
3	1	0	7/20	280	800	0	520	520	-280	520	520
4	1	1/5	1/20	30	800	0	770	770	-30	760	760
5	1	1/5	2/20	60	800	0	740	740	-60	720	720
6	1	1/5	7/20	220	800	0	580	580	-220	520	520
7	1	2/5	1/20	20	800	0	780	780	-20	760	760
8	1	2/5	2/20	50	800	0	750	750	-50	720	720
9	1	2/5	7/20	170	800	0	630	630	-170	520	520
10	1.5	0	1/20	80	800	0	720	720	-80	760	720
11	1.5	0	2/20	160	800	0	640	640	-160	720	640
12	1.5	0	7/20	560	800	0	240	240	-560	520	240
13	1.5	1/5	1/20	60	800	0	740	740	-60	760	730
14	1.5	1/5	2/20	130	800	0	670	670	-120	720	650
15	1.5	1/5	7/20	450	800	0	350	350	-450	520	290
16	1.5	2/5	1/20	50	800	0	750	750	-40	760	730
17	1.5	2/5	2/20	100	800	0	700	700	-100	720	670
18	1.5	2/5	7/20	340	800	0	460	460	-340	520	350

Nous montrons que pour les plus fortes fréquences de sécheresse, la demande d'assurance diminue, comme dans la partie droite de la courbe ci-dessus.

TABLE 18 – Estimation en panel des déterminants de la demande d'assurance

	(1)	(2)	(3)	(4)	(5)
m	-0.211***	-0.208***	-0.208***	-0.418***	
	(0.0491)	(0.0518)	(0.0504)	(0.098)	
p	-0.235***	-0.236***	-0.235***	-0.431**	-0.248**
	(0.0542)	(0.0592)	(0.0584)	(0.177)	(0.110)
					[0.0240]
r	-0.0909**	-0.0908**	-0.0909**	0.154	-0.0809
	(0.0437)	(0.0400)	(0.0396)	(0.115)	(0.0664)
					[0.2382]
Constant	1.066***	0.976***	1.059***	0.787	0.811***
	(0.0637)	(0.0965)	(0.0662)	(0.715)	(0.0319)
Effets fixes	Non	Village	Individu	Individu & jeu	Individu $\times$ session
Effets aléatoires	oui	oui	non	non	non
Observations	3009	3009	3009	3009	3009

Les erreurs standard avec bootstrap sont notées entre parenthèses avec clustering individu (col. 1 à 4), et avec clustering session (colonne 5). Les P-values avec wild boostrap et clustering session sont entre crochets (col. 5).
* $p < .1$, ** $p < .05$, *** $p < .01$

Plus largement, même si ce papier n'a pas été monté dans cet esprit, il conduit à réfléchir aux formes d'assurance agricole les plus adaptées aux besoins de paysans dans des contextes de sécheresse fréquente. Il existe une forme d'épargne traditionnelle très prisée des agriculteurs du Sahel, qui est le petit élevage, voire le bétail, qui permet de lisser les revenus entre les bonnes années (avec constitution d'un capital animal) et les mauvaises années (décapitalisation). Cette forme d'assurance, qui n'a pas la caractère mutuel de l'assurance, présente toutefois plusieurs intérêts de taille : (i) l'équivalent de la prime d'assurance n'est pas versée à un tiers mais reste sur la ferme ; (ii) il s'agit d'une épargne peu liquide (contrairement aux stocks de céréales) qui permet de résister aux fortes préférences pour le présent et à la pression sociale ; (iii) l'équivalent de l'indemnisation (la décapitalisation) n'est pas soumise au risque de base puisque le diagnostic de sécheresse se fait par le bénéficiaire.

5.2 Sécheresses et assistance alimentaire au Niger

Ce travail tiré d'une expertise pour l'Union Européenne est une étude d'impact de la politique nationale d'assistance alimentaire d'urgence au Niger, constituée de distributions gratuites ciblées de vivres et de ventes de céréales à prix modéré (VPM). Ce sont des politiques d'une grande importance en termes politiques et en termes de volumes distribués ou vendus à prix modéré. L'impact de cette politique n'avait pas été mesuré. Ce projet de publication se fonde sur des enquêtes sur grand échantillon dans la région de Maradi. Avec des enquêteurs Nigériens, nous avons enquêté 1000 ménages dans deux départements bénéficiaires de l'aide. La moitié de ces ménages environ a bénéficié de ces aides, l'autre non. Toute la difficulté est que les bénéficiaires n'ont pas été sélec-

tionnés au hasard, et ils diffèrent a priori des non bénéficiaires. La comparaison pure et simple des deux groupes après distribution peur donner des informations sur le profil des bénéficiaires, mais pas sur l'impact de la politique.

En 2020, je pensais retourner enquêter les mêmes ménages pour pouvoir identifier des effets fixes ménages, et donc séparer ce qui caractérise un ménage de manière structurelle et ce qui caractérise sa réaction à la politique ; C'est une méthode qui me semble la meilleure, mais les conditions sanitaires puis sécuritaires m'empêchent de faire cette deuxième enquête.

La piste que j'ai privilégiée est d'utiliser une variable instrumentale pour remplacer le fait d'avoir reçu l'aide, mais qui ne dépend pas de la volonté de l'Etat. La distance du ménage au point de vente est une variable intéressante parce qu'elle a manifestement un impact sur le fait de bénéficier de la politique (elle est corrélée au traitement) et elle est a priori indépendante de la variable d'impact recherchée (production, revenu) en dehors de la politique.

J'ai développé un modèle théorique de l'aide dont l'impact attendu est positif à court terme et négatif à long terme sur la production et le revenu agricole. A court terme, l'aide alimentaire permet aux ménages de maintenir une part significative de leur force de travail aux travaux de leur propre champ, au lieu de vendre leur force de travail pour se nourrir, ou de consacrer une part importante de leur temps à des activités -faiblement- génératrices de revenu non agricole de soudure comme la collecte et la vente de bois. A court terme, pour la majorité des ménages l'aide permet donc d'accroître la production. Mais à long terme, il est attendu que la baisse des prix annuelle due aux politiques d'assistance soit anticipée par la population agricole et que la baisse de profitabilité induise une baisse de la production.

On définit une fonction d'offre locale du village j au moment t qui dépend de la somme des stocks existant dans le village S_{jt}, du prix p_{jt}, et du volume de VPM z_{jt}.

$$y_{jt} = f(S_{jt}, p_{jt}) + z_{jt}$$

où $S_{jt} = \sum_{n=1}^{N} s_{jt,n}$, N étant le nombre de ménages du village et $s_{jt,n}$ le stock du ménage n.

On définit la demande locale q_{jt} de la même façon qui dépend du prix et du revenu disponible localement R_{jt} qui est la somme des revenus des ménages $R_{jt} = \sum_{n=1}^{N} r_{jt,n}$

$$q_{jt}(R_{jt}, p_{jt})$$

L'équilibre du marché du village nous confirme l'impact des VPM sur le prix local et étant donné la fonction de demande, sur la consommation de court terme.

$$f(S_{jt}, p_{jt}) + z_{jt} = q_{jt}(R_{jt}, p_{jt}) \quad \rightarrow \quad dp_{jt}/dz_{jt} = \frac{1}{\frac{\partial q_{jt}}{\partial p_{jt}} - \frac{\partial f_{jt}}{\partial p_{jt}}} < 0$$

Les effets de long terme supposent d'intégrer dans les choix d'intrant les prix anticipés. Pour les ménages qui pourraient conserver des céréales jusque la soudure, les choix d'investissement et la vente sont espacés d'un an.

Etant donné z_{jt+1}, on choisit x_{ijt} qui maximise π_{ijt+1}, oùt représente une année.

Le principe est de faire varier z_{jt+1} et de regarde comment répond x^*_{ijt}

$$\max_{x_{ijt}} \pi_{ijt+1} = Ep(z_{jt+1})y_{ijt+1}(x_{ijt}) - \omega x_{ijt}$$
$$r_{ijt} \geq \omega x_{ijt} + p(z_{ijt})m_{ijt}[p(z_{jt})] + \overline{p}z_{ijt}$$
$$m_{ijt} + z_{ijt} = q_{ijt}$$

où z_{ijt} est la part de VPM z_{jt}achetée par le ménage i et limitée par quota local, $y_{ijt+1}(x_{ijt})$ est la fonction de production du ménage i,ω est le prix de l'engrais, $m_{ijt}[p(z_{jt})]$ est la demande de céréales au prix du marché et $\overline{p}$ est le prix des VPM. $Ep(z_{jt+1})$ est le prix anticipé en soudure de l'année prochaine qui dépend des VPM de l'année prochaine. L'anticipation naïve que l'on utilise est $Ep(z_{jt+1}) = p(z_{jt})$.

La résolution donne deux solutions distinctes :

Pour les plus aisés ($r_{it} > \omega x^*_{it} + p(z_{jt})m_{ijt}[p(z_{jt})] + \overline{p}z_{ijt}$)), les VPM réduisent l'utilisation d'engrais :

$$dx_{ijt}/dz_{jt} = -\frac{\omega}{p'y_{ijt}"} \leq 0$$

Pour les plus pauvres, $r_{ijt} = \omega x_{jit} + p(z_{jt})m_{ijt}[p(z_{jt})]$, les deux cas sont possibles, selon que l'effet d'incitation négative des VPM domine ou non l'effet positif de relâchement des contraintes de liquidité pour l'achat d'engrais.

$$\frac{dx_{ijt}}{dz_{jt}} = \frac{1}{\omega}[\underbrace{-p'.m_{ijt}}_{\geq 0} + \underbrace{p - \overline{p}}_{\geq 0} - \underbrace{pq'_{jit}p'}_{\geq 0}]$$

La table ci-dessous montre la répartition des ménages qui ont conservé des stocks jusqu'à la soudure. Il s'agit d'un faible nombre, mais qui joue un rôle dans l'analyse.

TABLE 19 – stock mil avril (kg)

	N	Moyenne	Ec-type	Minimum	Maximum
stock =0	1012	0	0	0	0
0< stock<200	372	80	49	3	192
$200 \leq stock < 500$	111	270	75	200	450
$500 \leq stock < 1000$	38	598	106	500	815
$1000 \leq stock$	18	1426	412	1000	2400

Le modèle estimé par variable instrumentale est celui-ci

$$y_{it} = \alpha + X_i\beta + \gamma\hat{T}_{t-1} + \epsilon_{it}$$

$$T_{t-1} = a_0 + a_1 distancePV_{t-1} + a_2 PV -_{t-1} + \mu_{it}$$

ou T_{t-1} est le traitement (accès aux VPM l'année précédente), $distancePV_{t-1}$ est la distance du ménage au point de vente des VPM, c'est l'instrument principal, et PV_{t-1} est une dummy qui vaut 1 si le village était un point de vente en 2017, c'est l'instrument secondaire et X_i est

un vecteur de variables de contrôle. L'hypothèse principale est que la distance modifie seulement l'exposition au traitement mais n'a pas d'effet direct sur la production (condition d'exclusion). L'hypothèse de surridentification est vérifiée.

TABLE 20 – première étape, instrumentation

Variable	coeff. estimés	Erreur type	Valeur du test t	Pr > |t|
Intercept	0,69***	0,038	17,98	<,0001
$distancePV_{t-1}$	-0,01**	0,005	-2,14	0,03
PV_{t-1}	0,052	0,046	1,12	0,26

* $p < .1$, ** $p < .05$, *** $p < .01$

TABLE 21 – première étape, instrumentation

Intercept	5539.58	8502.06	0.65	0.51
achat de vpm-2017 (T_{t-1})	-1385.5**	673.89	-2.06	0.04
ethnie-peulh	-145.20	310.79	-0.47	0.64
position-Latitude	-366.26	620.49	-0.59	0.55
NB-membres	27.85***	7.49	3.72	0.0002
age	7.43**	3.10	2.40	0.016
vaches-pre-soudure	99.11***	18.44	5.37	<.0001
alphabetisé	40.47	88.85	0.46	0.64
nb-motos	-50.57	77.26	-0.65	0.51

Test des restrictions de suridentification F=0.23, Pr>F=0.634

* $p < .1$, ** $p < .05$, *** $p < .01$

Il s'agit de résultats préliminaires qui doivent être explorés dans plusieurs dimensions, mais ces résultats sont compatibles avec les prédictions théoriques ci-dessus.

Là aussi, l'efficacité de la politique d'aide aux populations les plus pauvres ou les plus touchées par le climat est fortement impactée par les redistributions des aides au sein des familles et des villages, de même que par la volonté de l'Etat de distribuer ces aides dans toutes les communes du pays, même les communes excédentaires, mêmes les bonnes années. Cela conduit à diluer l'aide et peut même engendrer des effets pervers dans les zones excfédentaires. Cette dilution résulte de redistributions entre les besoins identifiés et les populations effectivement bénéficiaires. Ces redistributions résultent en grande partie d'une pression sociale intra-village et nationale qui amoindrie l'efficacité de la politique (et la rend socialement plus acceptée).

5.3 Impact de la pression sociale sur les redistributions et l'investissement (direction de thèse envisagée)

L'objectif de ce projet articulé autour d'une direction de thèse est de mesurer l'impact de la pression sociale sur les redistributions intra-groupes en Afrique, et sur les investissements des paysans.

Il existe des expériences ou des études de cas qui mesurent des comportements d'évitement de la pression sociale de la part des individus qui cherchent à ne pas redistribuer autant qu'ils le feraient s'ils étaient soumis à la pression sociale sans évitement (Baland et al., 2011; Jakiela

and Ozier, 2016; Goldberg, 2017). Mais il n'existe pas à notre connaissance d'expériences qui mesurent la redistribution elle-même en fonction de la pression sociale.

Pour ce faire, la ou le doctorant.e mettra au point probablement deux sessions d'économie expérimentale en Afrique dans un pays à définir (éventuellement le Sénégal ou en Afrique de l'Est où des phénomènes similaires de pression sociale ont été décrits).

La première expérience visera à mesurer l'impact de la pression sociale sur les redistributions intra-village. Il s'agira de faire varier arbitrairement la pression sociale autour de chaque individu, et d'observer la modification de ses décisions de redistribution. La série des décisions à prendre par les paysans sera mise au point par la ou le doctorant.e de façon à tester une hypothèse qu'il ou elle aura formulée en amont en fonction de ses lectures et de l'objectif général mentionné ci-dessus.

Une trame d'expérience possible est la suivante. Un groupe de n paysans d'un même village reçoivent une dotation aléatoire (en monnaie locale) par tirage sans remise, constitué d'un montant élevé pour un seul paysan et de gains faibles pour les $n-1$ autres. Le joueur ayant tiré le gain élevé peut décider de redistribuer ou non une partie de son gain à qui il veut. En faisant varier le nombre de joueurs à faible gain de manière aléatoire, on fait varier la pression sociale autour du joueur au gain élevé. On anticipe que lorsque le nombre de joueurs augmente, le montant redistribué augmente, mais peut-être jusqu'à un certain point où le nombre de joueurs à faible gain devient trop important.

L'impact pourra être estimé par simple régression linéaire, éventuellement avec des variables de contrôle enregistrées par rapide survey (age, sexe, pratique de l'irrigation...), ou par panel si chaque joueur prend plusieurs décisions.

Une deuxième expérience envisagée dans le cadre de cette thèse visera à mesurer l'impact de la pression sociale sur les investissements des agriculteurs.

Une trame de départ possible sera la suivante. Chaque agriculteur d'un groupe de n agriculteurs reçoit une dotation aléatoire et inconnue des autres, mais chacun sait que le tirage comprend une dotation élevée et $n-1$ dotations faibles. Après avoir reçu sa dotation, chaque agriculteur décide d'investir cette dotation dans une production agricole à rendement certain et dont le produit sera rendu public, ou de conserver la dotation cachée jusqu'à la fin du jeu. Le gain après production pourra ou non être redistribué, à la discrétion du producteur. On fait varier arbitrairement n pour simuler une variation de la pression sociale (le traitement), et on observe l'investissement. On s'attend à ce que l'investissement diminue quand la pression sociale augmente.

L'enseignement de ce type d'expérience, si elle réussit, sera de montrer que l'investissement dans l'agriculture en Afrique ne dépend pas seulement de la possibilité d'investir (accès au crédit ou mise à disposition de technologie), mais de l'incitation à investir, qui dépend de la redistribution future que le producteur anticipe.

Enfin, la thèse comportera une partie d'analyse des politiques d'aide à l'investissement reposant sur les conclusions que la ou le doctorant.e aura tirée des expériences ci-dessus, par exemple par un modèle théorique. La contribution recherchée pourra être en lien avec la litérature sur la liquidité des biens dans le cadre du self control (Laibson, 1997), mais avec une redistribution facultative. Une piste pourrait être de comparer l'efficacité de deux types de politiques d'aide à l'investissement, une politique à haut rendement mais à produit liquide (comme une subvention

des engrais) et une politique à rendement faible mais à produit immobilisé (comme une subvention à l'achat de bétail). Peut-être faut-il encourager les investissements moins liquides pour les soustraire à la pression sociale ?

5.4 Impact du changement climatique sur la pression sociale et les politiques d'adaptation (direction de thèse envisagée)

Ce projet vise à mesurer l'impact du changement climatique sur les redistributions intra-groupe et les politiques d'adaptation. En cas de sécheresses plus fréquentes ou plus marquées, les adaptations des paysans peuvent être un investissement pour ceux qui le pourront et qui le voudront. Par exemple, l'investissement dans l'irrigation peut être une solution intéressante pour les agriculteurs qui ont accès à un cours d'eau ou un point d'eau suffisant. Mais ce changement climatique engendre aussi potentiellement un déplacement de la pression sociale de la part de ceux qui n'ont pas accès à un point d'eau envers ceux qui ont accès à un point d'eau. Cette nouvelle pression sociale ou la perspective de cette pression sociale peut dissuader certains producteurs d'investir, ou elle peut modifier le point d'équilibre de l'investissement optimal.

En utilisant les enseignements de la première thèse proposée ci-dessus, j'aimerais proposer un sujet de recherche pour étudier ce dilemme. Faut-il s'adapter ou laisser les autres le faire ? Ceci pourra être modélisé par un modèle économique destiné à clarifier les effets suggérés ci-dessus. Et une expérience économique pourra être proposée pour tester un effet en particulier. Par exemple, la variable climatique pourra être simulée par une loterie (sécheresse / pluie avec une probabilité connue) qui impacte les gains des paysans différemment selon qu'ils investissent dans l'irrigation ou pas (cf matrice des gains indicative ci-dessous). Le changement de climat pourrait être représenté par un changement de la probabilité de sécheresse p. Après chaque tirage du climat, les producteurs recevraient leurs gains, et auraient la possibilité de les redistribuer. Plus p augmente, plus les occurrences de gain nul augmentent, ce qui crée deux incitations contraires : l'investissement en irrigation est de plus en plus rentable, mais l'espérance de redistribution pour ceux qui ont investi est de plus en plus forte, ce qui peut éventuellement décourager l'investissement. La résultante incertaine sera utilisée dans la réflexion sur l'adaptation au changement climatique.

TABLE 22 – Matrice des gains et des probabilités de sécheresse

	sécheresse	pluie
	p	$1-p$
avec irrigation	1000 Fcfa	1000 F cfa
sans irrigation	0	1000 Fcfa

La mesure de l'impact pourra se faire par une régression de panel à effets fixes dès lors que chaque producteur prend plusieurs décisions. On pourra estimer à la fois l'impact de p sur l'investissement et l'impact de p sur la redistribution.

Ce travail devra inclure une réflexion sur les politiques d'aide à l'adaptation. Une première piste de recherche pourra porter sur l'analyse d'une politique de compensation des redistributions

imposées par la pression sociale sous forme d'une aide à l'adaptation (par exemple une aide à l'irrigation). Une autre piste pourra être de viser à réduire la pression sociale sur ceux qui investissent dans l'adaptation en réduisant les inégalités dans l'accès à la dotation en eau. Même si l'inégalité de base dans l'accès à l'eau est probablement acceptée par les villageois car elle fait partie d'un équilibre socio-politique local lié aux éthnies, aux périodes d'arrivées des familles dans le village, etc., la modification de ces inégalités due au changement climatique pourrait remettre en cause l'acceptation de cet équilibre et être une occasion de réduire l'inégalité d'accès à l'eau d'irrigation. Aujourd'hui, l'accès aux points d'eau d'irrigation n'est pas toujours perçue comme un enjeu majeur par les agriculteurs qui vivent d'agriculture pluviale. Mais si les sécheresses deviennent plus fréquentes et plus dures, la pression pour le partage de l'accès aux points d'eau pourrait s'accroître.

6 Conclusion

Mes travaux établissent un lien entre des comportements de ménages ruraux du Sahel et l'insécurité alimentaire saisonnière de ces ménages. Ces comportements semblent conduire à une plus grande insécurité alimentaire en soudure, mais s'interprètent comme des stratégies pour échapper à la pression sociale (à la suite de Di Falco and Bulte (2011); Goldberg (2017). Un premier papier montre que la préférence pour le présent réduit l'investissement des paysans (les plus impatients achètent moins d'engrais que les autres). Un second papier montre qu'une façon d'accroître l'investissement en engrais est de fournir l'engrais à crédit en début de soudure et de déduire ce crédit de la valeur de la production ; un troisième papier montre que les paysans ayant le biais pour le présent le plus élevé - les plus sujets à un épuisement des stocks prématuré par rapport à leur propre souhait - sont ceux qui utilisent le plus le warrantage comme moyen de self-control. Un quatrième papier en cours montre que l'utilisation du warrantage augmente la disponibilité alimentaire en période de soudure et la production l'année suivante. Un cinquième papier montre que la volatilité locale est atypique dans le sens d'une fréquence anormale des chutes de prix, et ceci s'explique par des erreurs d'anticipation conduisant aux déstockages tardifs. Un sixième papier montre que ce phénomène est plus important dans les villages les plus reculés.

Mes travaux futurs s'orientent vers l'évaluation des politiques de sécurité alimentaire au Sahel. Un septième papier évalue de manière expérimentale la demande d'assurance sécheresse (une politique de correction d'une défailllance de marché du risque climatique), et montre que la demande d'assurance contre les sécheresses diminue lorsque les sécheresses sont plus fréquentes. Le changement climatique pourrait donc nécessiter le renforcement des assurances traditionnelles au Sahel (comme l'élevage) plutôt que le développement de nouveaux outils plus performants ailleurs. Un huitième papier en cours évalue de manière quasi-expérimentale l'aide alimentaire au Niger et montre que les ventes de céréales à prix modéré sont faiblement ciblées et fortement sujettes à la pression sociale.

La mise en résonance de ces deux chantiers me conduit à me demander si les politiques publiques ne seraient pas plus efficaces si elles prenaient en compte les aspects comportementaux des ménages vulnérables qui cherchent à échapper à la pression sociale.

Les politiques de développement agricole ont tendance à partir du principe que les producteurs veulent investir mais n'en ont pas les moyens. Ces politiques se focalisent logiquement sur les défaillances de marché, ou le manque d'innovation qui freinent ces investissements. Mais tous les producteurs n'ont pas forcément pour but d'investir, parce que le devoir de redistribution des bénéfices issus de l'investissement est fort. La redistribution est souvent subie (Comola and Fafchamps, 2010).

Les politiques de développement devraient s'intéresser de plus près au devenir des retombées des investissements qu'elles encouragent. Une solution est de produire des bénéfices moins liquides, comme le bétail, des bénéfices immobilisés en période faste, comme le warrantage, ou des bénéfices nets du coût des investissements, comme dans le cas du coton, ce qui réduit l'assiette soumise à pression sociale.

A titre d'illustration, la différence entre les milliers de banques de céréales qui parsèment le Sahel comme des vestiges d'un développement rural un peu désincarné, et le warrantage qui est en croissance au Burkina et semble résister à la fin des projets, c'est que la clé des banques de céréales est dans le village et soumise à la pression sociale, alorsque les clés des entrepôts de warrantage est à la banque et donc soustraite à la pression sociale.

Références

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *econometrica*, 74(1) :235–267.

Abadie, A. and Imbens, G. W. (2016). Matching on the estimated propensity score. *Econometrica*, 84(2) :781–807.

Abay, K. A., Abate, G. T., Barrett, C. B., and Bernard, T. (2019). Correlated non-classical measurement errors,'second best'policy inference, and the inverse size-productivity relationship in agriculture. *Journal of Development Economics*, 139 :171–184.

Abdulai, A. (2000). Spatial price transmission and asymmetry in the ghanaian maize market. *Journal of development economics*, 63(2) :327–349.

Ainslie, G. (1975). Specious reward : a behavioral theory of impulsiveness and impulse control. *Psychological bulletin*, 82(4) :463.

Ainslie, G. (1986). Beyond microeconomics : Conflict among interests in a multiple self as a determinant of value. *The multiple self*, pages 133–175.

Akerlof, G. A. (1991). Procrastination and obedience. *The American Economic Review*, 81(2) :1–19.

Andersen, S., Harrison, G. W., Lau, M. I., and Rutstrom, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3) :583–618.

Ashraf, N., Karlan, D., and Yin, W. (2006). Tying odysseus to the mast : Evidence from a commitment savings product in the philippines. *Quarterly Journal of Economics*, pages 635–672. time preferences savings.

Badiane, O. and Shively, G. E. (1998). Spatial integration, transport costs, and the response of local prices to policy changes in ghana. *Journal of development economics*, 56(2) :411–431.

Baland, J.-M., Guirkinger, C., and Mali, C. (2011). Pretending to be poor : Borrowing to escape forced solidarity in cameroon. *Economic Development and Cultural Change*, 60(1) :1 – 16.

Barrett, C. (1997). Liberalization and food price distributions : Arch-m evidence from madagascar. *Food Policy*, 22(2) :155–173.

Barrett, C. B. (1996). On price risk and the inverse farm size-productivity relationship. *Journal of Development Economics*, 51(2) :193–215.

Barrett, C. B., Bellemare, M. F., and Hou, J. Y. (2010). Reconsidering conventional explanations of the inverse productivity–size relationship. *World Development*, 38(1) :88–97.

Bauer, M., Chytilová, J., and Morduch, J. (2012). Behavioral foundations of microcredit : Experimental and survey evidence from rural india. *American Economic Review*, 102(2) :1118–1139. time preferences credit.

Bazié, Y. G., Le Cotty, T., Maître D'Hôtel, E., Ouattara, D. O., and Sanou, A. (2020). ourquoi une relation positive entre taille des exploitations et productivité au burkina faso ? *Economie Rurale*, sous presse.

Bobenrieth, E., Wright, B., and Zeng, D. (2013). Stocks-to-use ratios and prices as indicators of vulnerability to spikes in global cereal markets. *Agricultural Economics*, 44 :1–10.

Burke, M., Bergquist, L. F., and Miguel, E. (2018). Sell low and buy high : Arbitrage and local price effects in kenyan markets. Working Paper 24476, National Bureau of Economic Research.

Cafiero, C., Bobenrieth, E., Bobenrieth, J., and Wright, W. (2011). The empirical relevance of the competitive storage model. *Journal of Econometrics*, 162 :44–54.

Carter, M. R. (1984). Identification of the inverse relationship between farm size and productivity : an empirical analysis of peasant agricultural production. *Oxford Economic Papers*, 36(1) :131–145.

Coate, S. and Ravallion, M. (1993). Reciprocity without commitment : Characterization and performance of informal insurance arrangements. *Journal of development Economics*, 40(1) :1–24.

Comola, M. and Fafchamps, M. (2010). Are gifts and loans between households voluntary ?

Deaton, A. and Laroque, G. (1992). On the Behaviour of Commodity Prices. *Review of Economic Studies*, 59(1) :1–23.

Di Falco, S. and Bulte, E. (2011). A dark side of social capital ? kinship, consumption, and savings. *Journal of Development Studies*, 47(8) :1128–1151.

Duflo, E., Kremer, M., and Robinson, J. (2011a). Nudging farmers to use fertilizer : Theory and experimental evidence from kenya. *American Economic Review*, 101(6) :2350–2390. time preferences fertilizer.

Duflo, E., Kremer, M., and Robinson, J. (2011b). Nudging farmers to use fertilizer : Theory and experimental evidence from kenya. *American Economic Review*, 101(6) :2350–90.

Feder, G. (1985). The relation between farm size and farm productivity : The role of family labor, supervision and credit constraints. *Journal of development economics*, 18(2-3) :297–313.

Foster, G. M. (1965). Peasant society and the image of limited good. *American anthropologist*, 67(2) :293–315.

Frechette, D. (1999). Stock-outs and supply response estimation under rational expectations. *European Review of Agricultural Economics*, 26(1) :59–77.

Fudenberg, D. and Levine, D. K. (2006). A dual-self model of impulse control. *American Economic Review*, 96(5) :1449–1476.

Gilbert, C. and Morgan, W. (2010). Food price volatility. *Philosophical Transactions of the Royal Society*, 365 :3023–3034.

Goldberg, J. (2017). The effect of social pressure on expenditures in malawi. *Journal of Economic Behavior & Organization*, 143 :173–185.

Gul, F. and Pesendorfer, W. (2001). Temptation and self-control. *Econometrica*, 69(6) :1403–1435.

Harris, C. and Laibson, D. (2001). Dynamic choices of hyperbolic consumers. *Econometrica*, 69(4) :935–957.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological science*, 15(8) :534–539.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5) :1644–1655.

Jakiela, P. and Ozier, O. (2016). Does africa need a rotten kin theorem ? experimental evidence from village economies. *Review of Economic Studies*, 83(1) :231.

Jayne, T., Myers, R., and Nyoro, J. (2008). The effects of ncpb marketing policies on maize market prices in kenya. *Agricultural Economics*, 38 :313–325.

Kahneman, D. and Tversky, A. (1979). Prospect theory : An analysis of decision under risk. *Econometrica*, 47(2) :263–91.

Kline, P. and Santos, A. (2012). A score based approach to wild bootstrap inference. *Journal of Econometric Methods*, 1(1) :23–41.

Kunreuther, H., Novemsky, N., and Kahneman, D. (2001). Making low probabilities useful. *Journal of risk and uncertainty*, 23(2) :103–120.

Kunreuther, H. and Slovic, P. (1978). Economics, psychology, and protective behavior. *The American Economic Review*, 68(2) :64–69.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2) :443–478.

Laibson, D. (2015). Why don't present-biased agents make commitments ? *The American Economic Review*, 105(5) :267–272.

Laury, S. K., McInnes, M. M., and Swarthout, J. T. (2009). Insurance decisions for low-probability losses. *Journal of Risk and Uncertainty*, 39(1) :17–44.

Le Cotty, T., Maitre D'Hotel, E., and Ndiaye, M. (2017). Transport costs and food price volatility in africa. *Journal of African Economies*, 26(5) :625–654.

Le Cotty, T., Maître d'Hôtel, E., Soubeyran, R., and Subervie, J. (2018). Linking risk aversion, time preference and fertiliser use in burkina faso. *Journal of Development Studies*, 54(11) :1991–2006.

Le Cotty, T., Maître d'Hôtel, E., Soubeyran, R., and Subervie, J. (2019). Inventory credit as a commitment device to save grain until the hunger season. *American Journal of Agricultural Economics*, 101(4) :1115–1139.

Le Cotty, T., Maître d'Hôtel, E., and Subervie, J. (2020). The impact of inventory credit on food security in burkina faso. *Unpublished*.

Leblois, A., Le Cotty, T., and Maître d'Hôtel, E. (2020). How might climate change influence farmers' demand for index-based insurance ? *Ecological Economics*, 176.

Loewenstein, G. and Prelec, D. (1992). Anomalies in intertemporal choice : Evidence and an interpretation. *The Quarterly Journal of Economics*, 107(2) :573–597.

Maître d'Hôtel, E. and Le Cotty, T. (2018). Why does on-farm storage fail to mitigate price volatility ? *Agricultural Economics*, 49(1) :71–82.

Maranz, D. E. (2001). *African friends and money matters : Observations from Africa*, volume 37. International Academic Bookstore.

McClelland, G. H., Schulze, W. D., and Coursey, D. L. (1993). Insurance for low-probability hazards : A bimodal response to unlikely events. *Journal of Risk and Uncertainty*, 7(1) :95–116.

Nyange, D. and Wobst, P. (2005). Effects of strategic grain reserve, trade and regional production on maize price volatility in tanzania : An arch model analysis. Technical report.

O'Donoghue, T. and Rabin, M. (1999). Doing it now or later. *American Economic Review*, 89(1) :103–124.

O'Donoghue, T. and Rabin, M. (2015). Present bias : Lessons learned and to be learned. *The American Economic Review*, 105(5) :273–279.

Platteau, J.-P. (2000). *Institutions, Social Norms and Economic Development*. Harwood Academic Publishers, Amsterdam.

Prelec, D. (2004). Decreasing impatience : A criterion for non-stationary time preference and "hyperbolic" discounting. *Scandinavian Journal of Economics*, 106(3) :511–532.

Samuelson, P. A. (1952). Spatial price equilibrium and linear programming. *The American economic review*, 42(3) :283–303.

Serra, T. and Gil, J. M. (2013). Price volatility in food markets : can stock building mitigate price fluctuations ? *European Review of Agricultural Economics*, 40(3) :507–528.

Slovic, P., Fischhoff, B., Lichtenstein, S., Corrigan, B., and Combs, B. (1977). Preference for insuring against probable small losses : Insurance implications. *Journal of Risk and insurance*, pages 237–258.

Strotz, R. (1956). Rev econ stud. *Rev. Econ. Stud.*, 23 :165.

Wassie, S. B., Abate, G. T., and Bernard, T. (2019). Revisiting farm size-productivity relationship : New empirical evidence from ethiopia. *Agrekon*, 58(2) :180–199.

Williams, J. and Wright, B. (1991). *Storage and commodity markets*. Cambridge University Press.

Wright, B. (2011). The economics of grain price volatility. *Applied Economic Perspectives and Policy*, 33(1) :32–58.

7 Glossaire

AFD (Agence Française de Développement)

ARCH (Autoregressive Conditional Heteroskedasticity)

ATE (Average Treatment Effect)

ATT (Average Treatment effect on the Treated)

CEEM (Centre d'Economie de l'Environnement Montpellier)

CEMAGREF (Centre d'Étude du Machinisme Agricole et du Génie Rural des Eaux et Forêts)

CIRAD (Centre de coorpération Internationale et de Recherche Agronomique pour le Développement)

Cired (Centre International de Recherche pour l'Environnement et le Développement)

CPF (Confédération Paysanne du Faso)

CSAE (Centre for the Study of African Economics)

DG DEVCO (Direction Générale du Développement et de la Coopération)

EAAE (European Association of Agricultural Economists)

ENSAIA (Ecole Nationale Supérieure d'Agronomie et des Industries Alimentaires)

ENSAR (Ecole Nationale Supérieur d'Agronomie de Rennes)

FARMAF (Farm Risk Management in Africa)

FCFA (Franc des colonies françaises d'Afrique)

FIDA (Fonds International de Développement Agricole)

IDDRI (Institut du Développement Durable et des Relations Internationales)

ITT (Intention To Treat)

LAMETA (Laboratoire Montpelliérain d'Economine Théorique et Appliquée)

LAQADS (Laboratoire d'Analyses Quantitatives Appliquées au Développelment au Sahel)

MCO (Moindres Carrés Ordinaires)

MOISA (Montpellier Interdisciplinary center on Sustainable Agri-food systems - Social and nutritional sciences)

NPK (Azote, Phosphore, Potassium)

PSE (Paris School of Economics)

RCT (Randomized Controlled Trials, ou Essais Randomisés Contrôlés)

SIAMETHOD (Sustainability Impact Assesment Method)

SMART (Structures, Marchés Agricoles, Ressources et Territoires)

Solagral (Solidarités Agricoles et Alimentaires)

SONAGESS (Société nationale de gestion des stocks de sécurité alimentaire du Burkina Faso)

UE (Union Européenne)

VPM (Ventes à Prix Modéré))

Inventory Credit as a Commitment Device to Save Grain Until the Hunger Season

T. Le Cotty, E. Maître d'Hôtel, R. Soubeyran, and J. Subervie

In January 2013, we collected data from 653 farmers in Burkina Faso, who were asked hypothetical questions about risk aversion and time discounting. Ten months later, these farmers were offered the opportunity to participate in an inventory credit system, also called warrantage, in which they receive a loan in exchange for storing a portion of their harvest as a physical guarantee in one of the newly-built warehouses of the program. We found that a significant number of farmers chose to store grain in the warehouse without taking the maximum amount allowed for a loan in return, and that farmers who exhibit a stronger present bias were significantly more likely to participate in the warrantage system than other, otherwise similar, farmers. We interpret these results as evidence that farmers use warrantage as a means to commit to saving a portion of their crop until the lean season. These results are in line with the main predictions of our theoretical model, which explicitly takes the hyperbolic nature of farmers' time preferences into account.

Key words: Commitment savings, inventory credit, hyperbolic discounting.

JEL codes: D14, O12.

In developing countries, banks and financial institutions generally shy away from lending to the agricultural sector because farmers are highly exposed to production risk and often lack collateral.[1] There is an abundant body of literature showing that credit constraints may exacerbate the negative effects of intra-annual grain price volatility, forcing farmers to sell their grain at a low price during the post-harvest season, and it has often been argued that providing credit access to poor farmers may help them smooth consumption.[2,3] In this context, inventory credit, also called warrantage, has emerged as a potential solution to this problem.

With warrantage, banks typically offer farmers an advance amounting to 80% of the market value of the amount of grain that they elect to secure in a certified warehouse over a six-month period. This is likely to improve farmers' food security in many ways. First, farmers who have access to credit may be more likely to engage in other income-generating activities, aiming not only to repay the loan but also to better cope with the lean season. Second, farmers who are able to repay the loan and get their collateral back can benefit from a possible increase in grain price. Third, farmers who store their crops as collateral until the time of loan repayment

T. Le Cotty is a research scientist at the French Agricultural Research Centre for International Development (CIRAD) and member of the CIRED research unit. E. Maître d'Hôtel is a research scientist at CIRAD and member of the MOISA research unit. R. Soubeyran and J. Subervie are both research scientists at the French National Institute for Agricultural Research (INRA) and members of the CEEM research unit. Funding for this research was provided by the European Union, with counterpart funding from AGRINATURA for the Farm Risk Management for Africa project, coordinated by CIRAD. This research would not have been possible without the full cooperation of the Confédération Paysanne du Faso. The authors are also grateful to the members of field teams for their outstanding collaboration. The authors especially thank the editor, Travis Lybbert, and two anonymous referees for their outstanding comments and suggestions. All remaining errors are the responsibility of the authors. Correspondence may be sent to: julie.subervie@inra.fr.

[1] See, among others, Bester (1987) and Hoff and Stiglitz (1990).

[2] See Stephens and Barrett (2011); Kazianga and Udry (2006); Dillon (2016); Casaburi and Willis (2016); Gross, Guirkinger, and Platteau (2017).

[3] See Burke, Bergquist, and Miguel (2018); Basu and Wong (2015); Fink, Jack, and Masiye (2014).

Amer. J. Agr. Econ. 101(4): 1115–1139; doi: 10.1093/ajae/aaz009
Published online April 24, 2019

escape the prevalent social pressure to share their harvest with kin and neighbors.[4]

Last but not least, these farmers circumvent the temptation to sell their grain in order to purchase goods of no long-term value, thereby enabling them to mitigate self-discipline problems that could otherwise limit their ability to save grain. Indeed, individuals who exhibit more impatience for near-term trade-offs than for future trade-offs usually think to be patient enough in the future to be able to save the harvest that they store on site; but when the time comes they may nonetheless fail to do so because they are tempted to use their crop for immediate consumption. For that reason, individuals who realize that they may revisit their choice in the future may seek for a way to "tie their hands" to prevent this from happening. For developing countries like Burkina Faso in which formal commitment savings mechanisms are lacking, warrantage is likely to provide an effective device in this regard. Warrantage can even be seen as a "hard commitment" device, according to the terminology proposed by Bryan, Karlan, and Nelson (2010) since it offers users the possibility of constraining their future self's consumption physically by storing their grain in a certified warehouse that is locked for six months and cannot be opened by anyone before the scheduled date. In this article, we offer a new rationale for the success of warrantage schemes based on the demand for commitment.

We implemented a warrantage system in Burkina Faso as part of the Farm Risk Management for Africa (FARMAF) project. We partnered with the Reseau des Caisses Populaires du Burkina Faso, a rural bank operating in Burkina Faso, and the Confédération Paysanne du Faso (CPF), a nationwide organization of farmers, to implement a warrantage system in the western region of Burkina Faso. In January 2013, a series of hypothetical choice experiments were implemented in the field to elicit measures of discounting and risk aversion for a random sample of 653 farmers spread across seven villages. In 2013, each of the villages was provided a warehouse. In November 2013, each farmer living in these villages was offered credit in exchange for storing a portion of their harvest as collateral in one of these warehouses, with no opportunity to access the stored grain for a period of six months. We collected data on farmers' participation in the system in 2013 and again in 2015. We found that farmers electing to engage in warrantage stored a quite large portion of harvested crops—around 30%. Moreover, we found that a significant proportion of participants chose to store without taking out a loan, a behavior that cannot be explained by the liquidity constraint. One of the main contributions of this article is thus to provide evidence of a link between farmers' risk and time preferences and participation in the system.

We develop a theoretical model in which the farmer is sophisticated with respect to present bias and makes decisions about how to allocate his harvest for various uses. We consider a three-period multi-self game in which participation in warrantage provides the farmer with a means to constrain his futures selves. The first self chooses to participate or not in the system, as well as the quantity of grain to be stored in the warehouse and the amount of the loan (no more than 80% of the value of the collateral); the second self can consume the grain stored at home but has no access to the grain stored in the warehouse; finally, the third self repays the loan and the interest, and receives the collateral back. The model provides four main results. First, there is a positive relationship between present-bias and participation into the warrantage scheme. Second, participants in warrantage are likely to fall into three categories: those who stored grain and borrowed the maximum amount allowed for a loan, those who stored grain and borrowed less than the maximum amount allowed for a loan, and those who stored grain without taking a loan. Third, farmers who store without taking the maximum loan cannot be time-consistent. Fourth, farmers who exhibit a strong present bias (whose hyperbolicity exceeds a certain threshold) may find it optimal to use warrantage even when it is more profitable to store grain at home.

We then match measures of farmers' risk aversion and time preferences with observed adoption of warrantage. We capture this

[4] Several recent studies indeed suggest that individuals living in poor communities often feel obligated to support relatives and neighbors (Platteau 2000; Barr and Genicot 2008; di Falco and Bulte 2011) and that those who anticipate that their income will be "taxed" by neighbors may choose to spend their wealth quickly (Goldberg 2017) or to hide part of it (Jakiela and Ozier 2016) in order to escape solicitations. Baland, Guirkinger, and Mali (2011) also suggest that excess borrowing is a strategy used by some individuals in order to signal to their peers that they are cash constrained and cannot respond to their demands.

relationship in a regression that includes a range of observable individual characteristics and village-year dummies. In line with the main prediction of the theoretical model, we find that farmers who exhibited hyperbolic preferences were significantly more likely to engage in the system. We interpret this result as evidence that time-inconsistent farmers use inventory credit as a means to commit to saving a portion of their crop until the hunger season. This result suggests that inventory credit is likely to provide support for people who wish to protect their harvest from their own, possibly short-sighted, impulses. While we cannot entirely rule out the possibility that this result arises due to an unobserved factor affecting both experimental measures of time and risk preferences, as well as warrantage adoption, it is worth noting that our findings are consistent with recent studies, suggesting that present-biased people may be particularly willing to engage in commitment devices in order to mitigate the anticipated impatience of their future selves.

Many theoretical models, such as the quasi-hyperbolic discounting model of Laibson (1997) or the temptation and self-control theory proposed by Gul and Pesendorfer (2001), imply a demand for commitment (see Bryan, Karlan, and Nelson 2010 for a review of the literature).[5] These models predict that individuals who exhibit more impatience for near-term trade-offs than for future trade-offs, and are sophisticated enough to realize this, will engage in commitment devices in order to increase their welfare (O'Donoghue and Rabin 1999).[6] Moreover, in the empirical literature, some recent studies have already established a link between hyperbolic preferences and decisions to engage in a commitment device (see Frederick, Loewenstein, and O'Donoghue 2002 for a review up to the early 2000s, and Sprenger 2015 for more recent papers). It is, however, difficult to find examples of pure commitment devices provided by the market in developing countries. Participation in a rotating savings and credit association (ROSCA) can be explained by a preference for commitment since joining a ROSCA makes defaulting very difficult unless one is prepared to bear the associated costs, which can be significant (Aliber 2001; Anderson and Baland 2002; Gugerty 2007; Ambec and Treich 2007; Basu 2011).

In practice, however, it remains difficult to determine whether people use the ROSCA because they perceive it as a commitment savings device or for other reasons. Evidence supportive of the idea that some people use savings devices for their commitment value would establish an empirical link between the use of a commitment device and the hyperbolic nature of the preferences of its users. Two seminal empirical studies do provide this type of evidence. In a study run in the Philippines, Ashraf, Karlan, and Yin (2006) showed that women who exhibited hyperbolic preferences were significantly more likely to open a commitment savings product. In South India, Bauer, Chytilova, and Morduch (2012) found that women who exhibited present-biased preferences were more likely to borrow from a self-help group than from a bank or a moneylender, interpreting this result as evidence that these women use self-help groups as a means to commit themselves to saving money each week.[7]

Our study builds on and extends this literature by providing the first field evidence that links time inconsistency to the decision to engage in a warrantage system, a promising development tool that is emerging in African countries. We show that there is heterogeneity in demand for a storage commitment device and that time-inconsistency can explain some of this heterogeneity. Our study thus provides new evidence regarding the relationship between time preferences, credit access, and storage choices among Burkinabe farmers, and presumably among farmers in sub-Saharan Africa more generally.

The article proceeds as follows. The next section describes the main features of the warrantage system that we implemented in

[5] Several papers have studied the theoretical properties of hyperbolic discounting (Phelps and Pollak 1968; Laibson 1997). Other approaches to modeling problems of temptation and self-control include Gul and Pesendorfer (2001), Fudenberg and Levine (2006), and Banerjee and Mullainathan (2010).

[6] Bernheim, Ray, and Yeltekin (2015) theoretically show that some external commitment devices can undermine the effectiveness of internal self-control mechanisms.

[7] More recently, Giné et al. (2018) implemented artefactual field experiments in Malawi and showed that the revisions of money allocations toward the present are positively associated with measures of present-bias. In a developed-country context, Meier and Sprenger (2010) elicited individual time preferences using incentivized choice experiments in the laboratory and showed that present-biased individuals are more likely to have credit card debt.

Burkina Faso, while the subsequent section describes a theoretical model of a sophisticated hyperbolic farmer's decision to allocate the harvest between warrantage and alternative uses. The next section describes the surveys, followed by a section that focuses on hypothetical risk and time preference data. The following section discusses how experimental choices correlate with observed adoption of warrantage, while the subsequent section provides alternative explanations for the apparent link between time-inconsistency and participation in warrantage. In particular, we discuss the extent to which our findings may arise due to an unobserved credit constraint or social taxes. The final section concludes.

Context and FARMAF Project

Warrantage is not yet widespread in Africa—it emerged in Niger in the 2000's (Coulter and Onumah 2002) and has been developing in Burkina Faso since 2005.[8] A precondition for a warrantage system to emerge is that banks must be confident that the stored product will be available should they need to withdraw it. From a market demand perspective, farmers who are willing to store a portion of their harvest for a period of six months must also be confident that their collateral will be returned once they repay the loan. Thus, each stakeholder in the system relies on the existence of a reliable network of certified warehouses.

As part of the FARMAF project, we implemented a warrantage system in seven villages located in the Tuy and Mouhoun provinces, in the western region of the country (see figure 1). The FARMAF project is one of the first programs aiming to develop warrantage in the country.[9] Except for the initial cost of building the warehouse and the initial organizational costs, 95% of which were covered by the FARMAF project and 5% by farmers, the system runs without material or financial assistance and has continued to function since 2013.

The warehouses were built in the villages so that farmers can bring their bags themselves with bicycles, motorcycles, or donkey-pulled carts. The warehouses have a storage capacity of up to 80 tons, which means that 50 households can each deposit 16 bags of 100 kg. In November 2015, that is, after three seasons of warrantage, 85% of the storage capacity was reached. The warehouses are secured with two locks. The key to one of these locks belongs to the rural bank, and the other key belongs to the local farmers' organization. As a result of this dual-lock system, neither party can open the warehouse in the absence of the other.

The warrantage system was designed to correspond to the agricultural calendar (figure 2). In the warrantage system as we implemented it, farmers are allowed to store cereals, sesame, and peanuts. Farmers store mainly maize, followed by sorghum and millet, which are characterized by very similar price patterns.[10] In Burkina Faso, land preparation and sowing for maize, sorghum, and millet typically begin in June, and the crops grow during July and August, maturing between September and October.[11] Farmers who participate in the warrantage system receive a loan in November, which is often used to pay seasonal employees for cotton harvesting.[12] Farmers who are able to repay the loan get their collateral back in May, during the lean season when the price of grain is usually high.

Every year since 2013, farmers were solicited to deposit a portion of their harvest in one of these warehouses in exchange for a six-month loan. The rural bank does not lend more than 80% of the value of the inventory at the time of the loan. Should borrowers

[8] Warrantage shares some features with the warehouse receipt systems (WRS) that exist in Ghana, Tanzania, and Zambia, but WRS cannot be considered commitment devices because farmers who own a receipt are able to sell their grains whenever they wish (Coulter 2009).

[9] Previous programs include the warrantage program of the NGO SOS Sahel, which was carried out in eight provinces of Burkina Faso (Bam, Gnagna, Ioba, Loroum, Mouhoun, Namentenga, Nayala, and Sanmatenga) and the warrantage program of the NGO Comunità Impegno Servizio Volontariato (CISV), which was carried out in the provinces of Tuy and Ioba.

[10] Farmers may also store beans (niébé), but since the pre-storage drying process is much easier for grains than for beans, farmers tend not to store beans. Another reason why farmers store mainly maize is that maize yields are higher (maize responds better to fertilizer). Sorghum and millet are very much appreciated for self-consumption and traditional usages including making dolo (a kind of traditional beer), whereas maize is not only consumed but is also a cash crop. Cotton, the main cash crop, is not a possible candidate for warrantage, notably because a parastatal board controls the entire cotton sector.

[11] The length of the cropping cycle is around 100 days for maize and 120 days for millet and sorghum.

[12] We collected information on the use of the credit during a survey carried out in August 2016, that is, at the end of the third warrantage season.

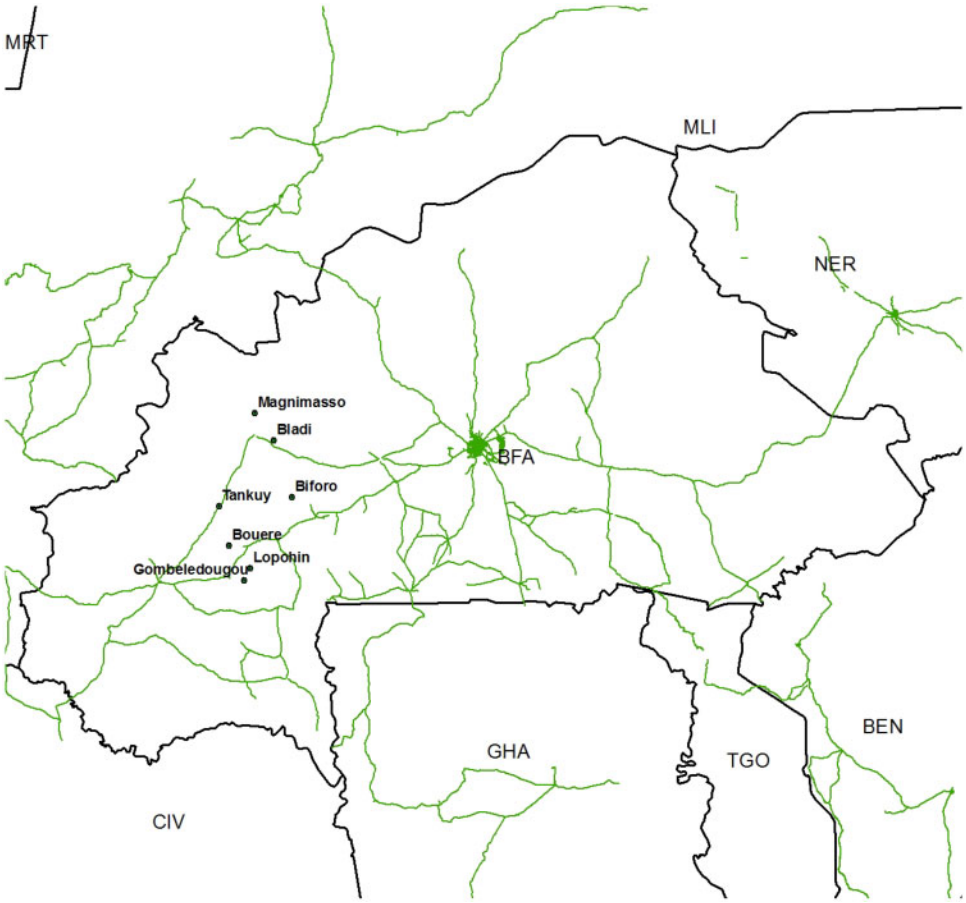


Figure 1. Location of participant villages

	June	July	August	Sept	Oct	Nov	Dec	January to April	May
Grain production	Tilling	Sowing Fertilizing	Plant growing Weeding Fertilizing		Harvesting				
Cotton production	Tilling	Sowing Fertilizing	Plant growing Weeding Fertilizing			Harvesting			
Inventory Credit (or warrantage)						Storage Credit delivery			Credit repayment Collateral restitution

Figure 2. Agricultural production and warrantage calendar in the Tuy and Mouhoun provinces

Note: Grain production refers to production of maize, millet, and sorghum.

default, this protects the rural bank even if the price of grain decreases by 20%, which is very unlikely to occur. The monthly interest rate charged by the bank is around 1%. The interest rate, as well as the value of the collateral, are determined by the

rural bank.[13] Farmers were also charged the cost of storage, which amounted to 100 CFA francs for each 100 kg bag of grain per month. This storage fee is based on information regarding previous warrantage programs that have been implemented in Burkina Faso and Niger, and includes the warehouse maintenance and the transaction costs incurred to deal with credit institutions (phone calls and travel from village to bank agencies). The borrower's name is written on each bag of grain that is deposited so that each farmer will be able to identify his deposit later. Farmers also have the opportunity to store grain without taking out a loan. When the loan matures, that is, in May, the bank demands repayment of the amount borrowed plus interest before authorizing the restitution of a farmer's collateral. If the farmer is not able to reimburse the loan and interests, the collateral is sold. In practice, the farmer must find a buyer and meet him at the warehouse on the repayment date. In this case, the farmer reimburses the bank and keeps what remains. If the farmer is unable to find a buyer on the repayment date, he is subject to a penalty: 10% of the total debt per day late. If the farmer defaults, the bank keeps the collateral. We do not have data on the proportion of farmers who had to sell their collateral in order to repay their loan. However, we do know that no farmer received penalties between 2013 and 2015.

Farmers must make a tradeoff between the benefits of participating in the warrantage system (such as access to credit and to a commitment device) and its direct and indirect costs (the opportunity cost of the collateral deposit, the obligation to pay storage costs at the time of deposit, the risk of not being able to reimburse the loan, the possible lack of understanding of how the system functions, the possible lack of trust, etc.).[14] In this system, the total cost of credit can easily be offset by the rising value of the collateral, which was around 40% on average over the last decade according to price surveys made by the Afrique Verte association on local markets.[15] However, the warrantage system may not be the cheapest alternative for immediate liquidity when the increase in grain prices is small. Indeed, warrantage is profitable only when the increase in the price of grain is sufficiently large compared to the interest rate. For instance, consider a household that owns some grain with a value of 10,000 CFA francs (post-harvest) and requires 8,000 CFA francs for immediate consumption. With warrantage, it must store 10,000 CFA francs as collateral in order to obtain a loan of 8,000 CFA francs and will be required to reimburse about 8,500 CFA francs after six months. If the price of grain does not increase over this time period, it will end up with 1,500 CFA francs (10,000–8,500). Without warrantage, it can sell grain to obtain 8,000 CFA francs immediately and store 2,000 CFA francs at home, ending up with 2,000 CFA francs six months later (continuing to consider the case in which the price of grain does not increase). In this case, selling on the market to obtain cash immediately is obviously more profitable than participating in an inventory credit system. We examine the theoretical mechanisms underlying the decision to participate in the warrantage system in the next section.

Theoretical Framework

In this section, we develop a theoretical model in which the farmer is sophisticated with respect to present bias and makes decisions about how to allocate his harvest for various uses. As we shall see, in this model, participation in warrantage provides the farmer with a means to constrain his future self.

A Multi-Self Game

We consider three periods in this model for two reasons. First, hyperbolic discounting comes into play when there are more than two periods. Second, in the context of our study, farmers rarely end up with a surplus of grain at the end of the year.[16] As a result, it is

[13] In 2013, the interest rate was 0.7% in Magnimasso, 0.8% in Lopohin, 1% in Tankuy, 1.5% in Bouéré, and 1.2% in Bladi, Biforo, and Gombélédougou. The mean value of a 100 kg bag of maize or sorghum as collateral was 10,000 F.

[14] Unfortunately, we lack data on the losses in quality and quantity of stored food due to pests. However, traditional storage techniques are generally considered to be reliable in this region, especially during the dry season when insects, pests, and mold are less likely to develop.

[15] Monthly local prices can be found at http://www.afrique-verte.org/ (accessed March 22, 2019).

[16] See Bernheim, Ray, and Yeltekin (2015) or Harris and Laibson (2001) for infinite horizon models that focus on the consumption decision problem of a budget-constrained individual with (quasi-) hyperbolic time preferences. Although we could have extended one of these models to include the specific features of warrantage, it would have led to a rather untractable model.

reasonable to model decisions regarding post-harvest investments over a crop year. The first period is the post-harvest season (November), when the farmer must decide whether or not to participate in the warrantage system. The intermediate period extends from December to April, when the farmer is not able to access any stored grain as collateral. The final period is the lean season (starting in May), when the farmer is required to reimburse the amount borrowed, as well as interest, before getting his collateral back.

The available harvest is a quantity of grain, denoted H and expressed in kilograms, which can be consumed by the family, stored on the farm in a traditional granary, sold at the market to purchase other goods, or stored in a warehouse as collateral. Let p_t be the price of grain at time t and q_t the quantity of grain consumed at time t. In periods 2 and 3, the (indirect) utility of the household is a constant relative risk aversion (CRRA) utility function $U(c_t) = \frac{(c_t)^{1-r}}{1-r}$, where $r > 0$ (and $r \neq 1$) is the risk aversion parameter and c_t is the value of the grain (expressed in CFA francs) that is consumed at time t. We assume, for the sake of simplicity, that there is no utility stream in period 1. The farmer's expected utility at time $t = 3$ is denoted $EU(c_3)$. The farmer's discounted expected utility at time $t = 2$ is

$$(1) \quad EU_2 = EU(c_2) + \frac{1}{1+\rho_1} EU(c_3)$$

where ρ_1 is the discount rate of the second-period self (or Self 2), applied to the utility stream that he receives in period 3. The farmer's expected utility at time $t = 1$ is

$$(2) \quad EU_1 = \frac{1}{1+\rho_1} EU(c_2) + \frac{1}{1+\rho_2} EU(c_3)$$

where ρ_1 (resp. ρ_2) is the discount rate of the first-period self (Self 1), applied to the utility stream that he receives over period 2 (resp. period 3).

In this model, hyperbolic discounting arises from the fact that $\frac{1}{1+\rho_2}$ does not necessarily equal $\left(\frac{1}{1+\rho_1}\right)^2$. When $\frac{1}{1+\rho_2} < \left(\frac{1}{1+\rho_1}\right)^2$, the farmer has (present-biased) hyperbolic preferences. Self 1 and Self 2 disagree on the quantity of grain that the farmer will consume in period $t = 2$ (Self 2 wants to consume a larger quantity of grain than does Self 1). In this situation, Self 1 may seek for a way to "tie Self 2's hands" to prevent him from doing so. Let us write the hyperbolic discounting parameter, denoted h, as a ratio of the discount factors: $h = -\frac{\left(\frac{1}{1+\rho_1}\right)^2}{\frac{1}{1+\rho_2}}$, with $h \geq -1$. If $h = -1$, the farmer has standard exponential time preferences, and $\frac{1}{1+\rho_2} = \left(\frac{1}{1+\rho_1}\right)^2$. If $h > -1$, the farmer has (present-biased) hyperbolic preferences, and $\frac{1}{1+\rho_2} < \left(\frac{1}{1+\rho_1}\right)^2$. Note that this model is strictly equivalent to the $\beta\delta$ model, where $\frac{1}{1+\rho_1} = \beta\delta$ and $\frac{1}{1+\rho_2} = \beta\delta^2$ and then $h = -\beta$.

At time $t = 1$, the farmer decides whether or not to participate in the warrantage system. If he opts to participate, he chooses the quantity of grain, denoted w, that is stored in the warehouse as collateral, and the loan rate, denoted θ, with $0 \leq \theta \leq 0.8$. Notice that the value of the loan is then $p_1\theta w$. In order to be able to get his grain back at time $t = 3$, the farmer must reimburse the principal amount of the loan as well as the interest $(1+i)p_1\theta w$, where i is the interest rate.

In order to take into account the difference between returns to warrantage and returns to alternative investments (whether on-farm storage or investment in a small business), we assume that the return to the grain stored in the warehouse as collateral equals $1 - \sigma$, times the return to the grain that is neither stored in the warehouse nor consumed, where σ refers to the costs of warrantage and $0 < \sigma < 1$.

In order to keep the model as simple as possible, we assume that the price of grain is low in the first two periods, that is, $p_1 = p_2 = \underline{p}$. On the contrary, we assume that the farmer is uncertain about the price of grain in the last period. The price of grain thus increases in period 3 up to $\bar{p}$ with a probability of $\pi > 0$ and remains low with a probability of $1 - \pi > 0$. Let us denote Δ as the maximum percent increase in the price of grain, that is, $\Delta = \frac{\bar{p} - \underline{p}}{\underline{p}}$.

At time $t = 1$, the farmer chooses w and θ such that his current period discounted utility (EU_1) is maximised and such that the first-period budget constraint $H - (1-\theta)w \geq 0$ holds and $0 \leq \theta \leq 0.8$. At time $t = 2$, the farmer chooses the consumption level c_2 that maximizes his period 2 discounted utility, with

$$(3) \quad c_2 = \underline{p} q_2$$

and he faces a budget constraint that is affected by the quantity of grain stored in the warehouse at time $t = 1$

$$(4) \quad H - (1-\theta)w - q_2 \geq 0$$

where the impact of committing to warrantage is clear, as w reduces the amount of grain available for second-period consumption.

At time $t = 3$, the household consumes all that remains of its grain

$$(5) \quad c_3 = p_3\Big(H - (1-\theta)w - q_2\Big) + p_3(1-\sigma)w - (1+i)\underline{p}\theta w$$

where $p_3\Big(H - (1-\theta)w - q_2\Big)$ is the value of savings at home, $p_3(1-\sigma)w$ is the value of the grain stored in the warehouse, and $-(1+i)\underline{p}\theta w$ is the reimbursement of the loan and the interest. The price of grain p_3 equals $\bar{p}$ with probability π and $\underline{p}$ with probability $1-\pi$.

Case with Hyperbolic Time Preferences

We solve the game played by the farmer and his future selves (and characterize the subgame perfect Nash equilibrium) through backward induction. We focus on the case where the maximum return to grain stored in the warehouse is larger than the reimbursement of the loan, that is, $(1-\sigma)(1+\Delta) > 1+i$.[17]

Optimal warehouse storage

In the case where the budget constraint of Self 2 is binding in equilibrium, we obtain clear-cut predictions regarding the effects of present bias on the optimal quantity of grain w^* that is stored as collateral. In particular, we find the following result:

PROPOSITION 1 [PRESENT BIAS & OPTIMAL WAREHOUSE STORAGE] *There exists a threshold $\underline{h} < 0$ above which the budget constraint of Self 2 is binding ($q_2^* = H - (1-\theta^*)w^*$). In this case, the optimal quantity of grain w^* increases with the hyperbolic preference parameter h:*

$$\frac{\partial w^*}{\partial h} > 0.$$

The proof is provided in the supplementary online appendix (proof A). The result given in the first part of proposition 1 arises because if the farmer is highly present-biased, and thus very impatient in the near future, his second-period self will consume a lot of grain. As a result, his budget constraint will be binding. The result given in the second part of proposition 1 arises because a farmer with sophisticated hyperbolic time preferences has the means to constrain his second-period self through warrantage.

The intuition behind proposition 1 is as follows. If the farmer is sufficiently present-biased, Self 1 stores on the farm the exact amount of grain that he wants that Self 2 consumes and he stores the remaining grain in the warehouse. In doing this, Self 1 guarantees Self 3 a sufficient level of consumption. The more the farmer is present-biased, the more he wishes to decrease Self 2's consumption level, and the more grain he stores in the warehouse.

Formally, the optimal share of grain that the farmer decides to store in the warehouse is given by:

$$(6) \quad \frac{w^*}{H} = \left[1 - \theta^* + \left[\frac{-h(1+\rho_1)(1-\theta^*)}{\pi[(1+\Delta)(1-\sigma)-(1+i)\theta^*]^{1-r} + (1-\pi)[1-\sigma-(1+i)\theta^*]^{1-r}}\right]^{\frac{1}{r}}\right]^{-1}$$

where θ^* is the optimal loan rate. In the appendix, we show that this rate does not depend on time preferences (ρ_1 and h). This characterization also leads to the prediction that the optimal quantity of grain w^* decreases with the impatience parameter ρ_1. In contrast, the effect of the risk aversion parameter on the optimal quantity of grain w^* remains ambiguous, since it appears to affect optimal storage in various ways.[18]

[17] Even in the event of a small increase in grain prices, the condition still holds for very high (and thus unlikely) values of σ. If this inequality does not hold, then the farmer would never be able to reimburse his loan. In such a case, the bank would never lend money.

[18] This is due to the fact that the risk aversion parameter in CRRA utility functions captures both risk aversion and intertemporal elasticity of substitution. It thus also plays a role in smoothing consumption over time.

Optimal loan rate

In the case where the budget constraint of Self 2 is binding in equilibrium, we find the following result:

PROPOSITION 2 [OPTIMAL LOAN RATE] *If $h \geq \underline{h}$, then the optimal loan rate is such that:*

Case 1: The farmer borrows the maximum amount allowed for a loan if her level of risk aversion is sufficiently low, that is, $\theta^* = 0.8$ if $r < \underline{r}$.

Case 2: The farmer borrows less than the maximum amount allowed for a loan if her level of risk aversion is intermediate, that is, $0 < \theta^* < 0.8$ if $\underline{r} \leq r \leq \bar{r}$.

Case 3: The farmer does not take out a loan if she is sufficiently risk averse, that is, $\theta^* = 0$ if $r > \bar{r}$

where $\bar{r} = \frac{Ln\left[\frac{\pi}{1-\pi}\frac{(1+\Delta)(1-\sigma)-(1+i)}{\sigma+i}\right]}{Ln[1+\Delta]}$ and $\underline{r} = \frac{Ln\left[\frac{\pi}{1-\pi}\frac{[(1+\Delta)(1-\sigma)-(1+i)]}{(\sigma+i)}\right]}{Ln\left[\frac{(1+\Delta)(1-\sigma)-0.8(1+i)}{1-\sigma-0.8(1+i)}\right]}$.

The proof of this result is provided in the supplementary online appendix (proof A). Proposition 2 reveals a typology of participants in the warrantage scheme. Participants can be divided into three groups, namely, those who store grain and borrow the maximum loan amount allowed, those who store grain and borrow less than the maximum amount allowed, and those who store grain without taking out a loan. This last group is of special interest for our study since it brings together participants who are explicitly seeking to use the commitment mechanism of the proposed scheme, that is, those farmers who have sufficiently hyperbolic time preferences and are highly risk averse.

Moreover, proposition 2 leads to the prediction that the optimal loan rate decreases with the risk aversion parameter in the case where level of risk aversion is intermediate, that is, when $\underline{r} \leq r \leq \bar{r}$. The reason for this is that taking a credit for investing is a risky choice: if the rate of return on the investment is lower than the interest rate, the farmer loses money. For this reason, risk-averse farmers will borrow less than others, *ceteris paribus*. The optimal loan rate is given by the following expression:

$$\theta^* = \frac{1-\sigma}{1+i}\frac{\left[\frac{\pi[(1+\Delta)(1-\sigma)-(1+i)]}{(1-\pi)(\sigma+i)}\right]^{\frac{1}{r}} - (1+\Delta)}{\left[\frac{\pi[(1+\Delta)(1-\sigma)-(1+i)]}{(1-\pi)(\sigma+i)}\right]^{\frac{1}{r}} - 1}. \quad (7)$$

Finally, and perhaps more surprisingly, proposition 2 predicts that the loan rate θ^* is independent of time preferences (as long as h is greater than $\underline{h}$). The reason for this is that borrowing is not an intertemporal choice as such in our model. Although borrowing means having more cash in hand today and assuming the burden of loan repayment in the future, it does not create any imbalance in the consumption path. This is because the farmer has the means to smooth his consumption: he can store grain either at home (which will increase his wealth in the second period) or in the warehouse (which will increase his wealth in the third period).

Case with Time-Consistent Preferences

To better understand the characteristics of farmers who store grain but do not take out the maximum loan amount, we examine the optimal loan rate θ^* in a model where the farmer has consistent time preferences, that is, $h = -1$. An important result arises from the comparison of the two models:

PROPOSITION 3 *In contrast to a present-biased farmer, a farmer having time-consistent preferences (i.e., $h = -1$) always chooses the maximum loan rate $\theta^* = 0.8$, whatever his level of risk aversion.*

The proof is provided in the supplementary online appendix (proof B). The intuition behind this result is as follows: a farmer who has time-consistent preferences does not benefit from warehouse storage per se because he does not value commitment devices, and he faces a cost $\sigma > 0$ per unit stored in the warehouse. Consequently, he will store the exact amount of grain necessary in order to obtain the loan amount he needs. In other words, he will choose the maximum loan rate.

Proposition 3 highlights the difference between the time-consistent model and the hyperbolic model. In the latter, a farmer can very well store without taking out the maximum amount of credit, provided he is sufficiently hyperbolic (i.e., $h \geq \underline{h}$) and sufficiently risk averse (i.e., $r > \bar{r}$), as stated in proposition 2. Thus, the mere fact that

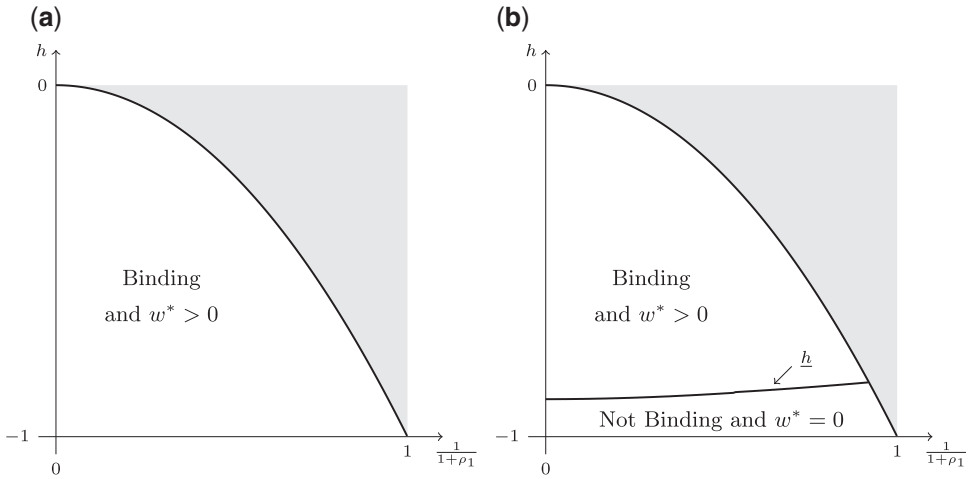


Figure 3. Decision to participate in warrantage under price certainty

(a) Case (i): $0.8(\Delta - i) - (1 + \Delta)\sigma \geq 0$ (b) Case (ii): $0.8(\Delta - i) - (1 + \Delta)\sigma < 0$
Note: This figure displays the areas for which the budget constraint of Self 2 is binding or not in equilibrium for $\pi = 1$ and $r = 0.5$. The parameter values used to plot panel (b) are $\sigma = 0.15$, $\Delta = 30\%$ and $i = 0.06$.

there are farmers in our sample who store grain without taking the maximum credit (or even without taking any credit) suggests that the hyperbolic model outperforms the time-consistent one in describing farmer decisions to participate in warrantage.

Case with Price Certainty

Finally, to better understand some farmers' decision to participate in warrantage when it is more profitable to store grain at home, we examine the particular case where the price increase is known with certainty (i.e., $\pi = 1$). Although proposition 1 states that there exists a threshold in present bias beyond which the budget constraint of Self 2 is necessarily binding, we were not able to characterize this threshold in the general case. It is, however, possible to do so in the particular case where the price increase is known with certainty, that is, $\pi = 1$. This model provides two results. First, risk aversion does not affect the optimal loan rate under price certainty and we thus always have $\theta^* = 0.8$.[19] Second, there are two situations in which warrantage appears as an optimal solution for the farmer, as shown in figure 3.

In case (i), we have $0.8(\Delta - i) - (1 + \Delta)\sigma \geq 0$, which implies that the increase in the price of grain is sufficient to offset the costs of warrantage (given that the farmer chooses the maximum loan rate). In this case, it is more profitable to participate in the warrantage scheme, and all farmers will do so. The budget constraint of Self 2 is binding, meaning here that Self 2 has the exact amount of grain he will consume.

In case (ii), we have $0.8(\Delta - i) - (1 + \Delta)\sigma < 0$, which implies that it is more profitable to store grain at home. Farmers whose hyperbolic preference parameter h is smaller than the threshold $\underline{h}$ do not use warrantage and the budget constraint of Self 2 is not binding. On the contrary, farmers whose hyperbolic preference parameter is above this threshold find it optimal to use warrantage in order to make the budget constraint of Self 2 binding because it is an efficient way to limit Self 2's consumption. We are able to (implicitly) characterize the threshold for any level of risk aversion and we are able to solve for an explicit formula in the case where the risk aversion parameter is $r = 0.5$ (which is the median value in our sample). In this case

[19] This result is due to the fact that the maximum quantity that can be stored through the warrantage system is not H but instead $H/(1 - \theta)$, due to the first period budget constraint $H - (1 - \theta)w \geq 0$. In practice, it would be possible for the farmer to find a grain seller, meet him at the warehouse at the time of the deposit and buy her grain with the loan. In that case, we would have w larger than H. Or, in case the consumption in period 1 would be positive and exogenous, H could be interpreted as the surplus rather than the harvest. In this case too, we could have w larger than H. If one assumes instead that $w \leq H$, the optimal θ may be lower than 0.8. We thank an anonymous referee for pointing this out.

we show that $\underline{h} = -1 + \sqrt{\frac{(1+\Delta)\sigma - 0.8(\Delta - i)}{0.2(1+\Delta)}\left(1 + \frac{1+\Delta}{(1+\rho_1)^2}\right)}$. The proof is provided in the supplementary online appendix (proof C).

In sum, our theoretical model highlights four important qualitative results regarding our understanding of farmer decisions on whether or not to participate in a warrantage program. First, the quantity of grain that is stored in the warehouse increases when the hyperbolic parameter increases (proposition 1). Second, participants are likely to fall into three categories, defined according to the model parameters, and the optimal loan rate decreases with risk aversion (proposition 2). Third, farmers who store grain without taking out the maximum loan are necessarily present-biased (proposition 3). Fourth, farmers who exhibit a strong present bias (whose hyperbolicity exceeds a certain threshold) may find it optimal to use warrantage even when it is more profitable to store grain at home—a result we highlighted in the particular case where the price of grain is known with certainty. In what follows, we show the extent to which our data are in line with these predictions. We provide a descriptive statistical analysis of our data, which shows that the typology presented in proposition 2 can be observed in the real world, and that the hyperbolic model should be preferred to the time-consistent model in explaining farmer decisions to participate in the warrantage scheme.[20] Our main empirical contribution is to provide a test for proposition 1 using our data.

Survey Data

Our main analysis is based on three surveys: a baseline survey run in January 2013 on a sample of 653 households living in the villages where the warehouses were later built, and two follow-up surveys, which were carried out among the subgroup of farmers who participated in the warrantage system in 2013 (the first year of the project) and those who participated in 2015 (the third year of the project).

Survey Procedure

All data were collected in cooperation with the CPF in 7 villages where the number of CPF members is known to be large. In these villages, we interviewed all CPF members, as well as a number of non-CPF members. For the baseline survey, we stratified the sample such that CPF members represented two-thirds of the total number of surveyed farmers. An average of 90 households were interviewed in each village. Twenty investigators and two supervisors were recruited for the data collection. Surveys and experiments were conducted in the Dioula language. The enumerators interviewed the heads of households, who were defined as the person responsible for making the farming decisions of the household.

Of the 653 farmers surveyed in January 2013, 103 (16%) accepted the offer to participate in the warrantage system in November 2013. Data on individual loan amounts and quantities stored were collected at the time of their deposits. These 103 farmers were also asked about the total quantity of crops harvested before warrantage.

We returned to the field at the end of 2015, at the end of the third round of the project. Of the seven villages enrolled in the program in 2013, one village had decided to leave the program and not participate in the 2015 follow-up survey. As a result, we were unable to determine the total number of participants in this village in 2015. Of the farmers surveyed in January 2013 in the 6 other villages, 167 (33%) had chosen to participate in the warrantage system in 2015. From these participants we collected another round of data on crop harvest, quantities stored, and loan amounts.

Sample Characteristics

Table 1 reports mean values for various farmer characteristics collected during the baseline survey. On average, the surveyed households are comprised of 11 members, 6 of whom are employed in farming activities. In almost all cases (98%), the household is headed by a man aged, on average, 42 years, who reports having received a formal education in 31% of cases. In the Tuy and

[20] However, we do not empirically test the existence of a relationship between the loan rate and the degree of risk aversion because this would require the use of a valid instrument, which we lack. Indeed, such a relationship cannot be estimated using a simple reduced form model because in regressing loan rates on risk aversion for farmers who chose to store grain in the warehouse, we are unable to observe the relationship for the sample as a whole. This is the standard problem of sample selection (Heckman 1979).

Table 1. Household Characteristics: Summary Statistics

Characteristics	Unit	Obs	Mean	Std. Dev.
Family size	number	653	11.19	7.61
Labor force	number	653	5.89	4.44
Sex	yes=man	653	0.98	0.13
Age	years	653	41.85	13.43
Education (literate)	yes=1	653	0.31	0.46
Cattle (none)	yes=1	653	0.30	0.46
Cattle (less than 10)	yes=1	653	0.58	0.49
Cattle (more than 10)	yes=1	653	0.11	0.32
Plow	number	653	1.63	1.42
Poultry	number	653	15.88	20.12
Total land area	ha	653	8.10	6.24
Maize area	%land area	653	0.17	0.18
Cotton area	%land area	653	0.32	0.21

Note: This table shows summary statistics for a set of characteristics measured in January 2013 during the baseline survey.

Table 2. Representativeness of the Sample

	Sample Used	National Survey
Family size number (number)	11.2	11.0
Age (years)	41.9	44.4
Education (=1 if literate)	0.3	0.3
Cattle (=1 if none)	0.3	0.2
Cattle (=1 if less than 10)	0.6	0.6
Cattle (=1 if more than 10)	0.1	0.2
Total land area (ha)	8.1	7.4
Maize area (ha)	1.4	1.5
Cotton area (ha)	2.6	2.6
Obs.	653	265

Note: This table displays summary statistics for main characteristics of farmers. Sample A refers to the sample used in the present study. Sample B refers to an extraction from a national agricultural survey led in 2013 by the Ministry of Agriculture of Burkina Faso. Sample B is representative of the Tuy and Mouhoun regions.

Mouhoun provinces, the main crops are cotton, maize, sorghum, millet, and sesame. On average, the surveyed households own 8 hectares of land and devote about 17% of their land to maize and about 32% to cotton.

We compare our data with the nationally-representative agricultural survey carried out by the Ministry of Agriculture of Burkina Faso in 2013 (see table 2). This survey includes 5,197 rural households that were randomly selected in each of the 45 provinces of Burkina Faso, among which 265 households were located in the Tuy and Mouhoun provinces, where our project was implemented. Table 2 shows that average household characteristics are very similar between our sample and the households from the same geographic area that were included in the national survey. This suggests that, although we focused on CPF members for the study, our sample appears to be quite representative of households located in western Burkina Faso.

Participation in Warrantage

Table 3 provides detailed information for the subset of surveyed farmers who decided to participate in warrantage in 2013 and/or in 2015. Overall, farmers electing to engage in warrantage stored a large portion of harvested crops: about 28% on average in 2013 and 34% in 2015. Storage was comprised mainly of maize versus other staple food crops such as sorghum and millet. It is worth mentioning that the composition of the sample of participants corresponds with proposition 2. We indeed find that the participants in the scheme are divided into three groups. In 2013, 67 participants (65%) borrowed 80% of the value of their stored harvest (the maximum amount allowed for a loan), 26 participants (25%) borrowed less, and the remaining 10% chose to store without taking out a loan. The situation was slightly different in 2015, as 77 participants (50%) borrowed less than the maximum amount allowed for a loan, and the proportion of those who chose to store without taking out a loan was also much higher (25%). This is consistent with the theoretical result that a farmer can very well store without taking out the maximum amount of credit provided he is sufficiently hyperbolic and sufficiently risk averse (see proposition 2).

Tables 4 and 5 provide a simple calculation of the total cost and returns of warrantage in 2013 and 2015 for the average farmer of the

Table 3. Participation in Warrantage: Summary Statistics

	No loan 0%	< Max.]0%, 80%[	=Max. 80%	All
Participation in 2013				
Number of farmers	10	26	67	103
Average nb of maize bags stored	6	18.7	13.5	14.1
Average nb of sorghum bags stored	1.2	1.7	1.7	1.7
Average nb of millet bags stored	1	0.9	0.3	0.5
Average share of harvest stored (%)	32	42	22	28
Average amount of credit (kCFA francs)	0	89.2	124.7	103.6
Participation in 2015				
Number of farmers	38	77	38	167[a]
Average nb of maize bags stored	3.6	13.0	12.3	10.4
Average nb of sorghum bags stored	0.6	1.4	0.6	1.0
Average nb of millet bags stored	0.2	0.4	0.0	0.2
Average share of harvest stored (%)	29	39	35	34
Average amount of credit (kCFA francs)	0	80.9	136.1	84.3

Note: This table shows summary statistics for the three groups of participants: The "no loan" column refers to those who stored some grain without taking up a loan; the " < max." column refers to those who borrowed less than the maximum amount allowed for a loan, and the "= max." column refers to those who borrowed the maximum amount allowed (80% of the value of stored bags). Superscript [a] indicates that for 14 participants in 2015, data on the credit was not available and/or inconsistent, which results in missing data. Consequently, the number of participants by type of credit does not sum to 167.

Table 4. Costs and Returns of Warrantage in 2015

Parameters	No Loan 0%	< Max.]0%, 80%[	=Max. 80%	All
Interest rate (over 6 months)	0.06	0.06	0.06	0.06
Price increase (rate)	0.25	0.25	0.25	0.25
Unit value of bags (CFA francs)	10,857	10,857	10,857	10,857
Storage costs (unit cost over 6 months)	600	600	600	600
Number of bags stored	3.6	13	12	10
Loan rate	0.00	0.44	0.80	0.42
Net gain from warrantage				
Gain from storage	9,771	35,285	32,571	27,143
Storage cost	2,160	7,800	7,200	6,000
Reimbursement of loan	0	3,821	6,412	2,805
Net gain	7,611	39,190	45,016	29,737
Net gain per bag	2,114	3,015	3,751	2,974
Net gain from storage at home at no cost				
Gain from storage	9,771	19,760	6,514	15,743
Storage cost	0	0	0	0
Net gain	9,771	35,285	32,571	27,143
Net gain per bag	2,714	2,714	2,714	2,714
Relative gain of warrantage (vs home)				
Total relative gain	−2,160	3,905	12,445	2,595
Relative gain by bag	−600	300	1,037	259

Note: This table compares the costs and returns of warrantage for maize in 2015. In 2015, the price of grain increased by 25%. The loan rate and the number of bags stored are mean values computed in each subgroup of participants, namely those who stored grain without taking a loan, those who stored grain and borrowed less than the maximum amount allowed for a loan, and those who stored grain and borrowed the maximum amount allowed for a loan. The value of a maize bag is the average price that was used in the seven warehouses to value the collateral at the time of the deposit. We calculate the net gain of warrantage by taking the added-value of grain stored in the warehouse after six months ("gain from storage"), minus the storage costs (100 F per bag and per month), minus the reimbursement of the loan, which includes the capital and the interest (about 1% per month). We calculate the net gain of storing the same quantity on farm at no cost.

sample and in each category of borrowing. In 2015, the price of grain increased by 25%. The total cost of credit was easily offset by the rising value of the collateral, as shown in table 4: the net gain of warrantage for the average farmer who stored 10 bags of maize in the warehouse and borrowed 42% of the value of the quantity stored, was about

Table 5. Costs and Returns of Warrantage in 2013

Parameters	No Loan 0%	< Max.]0%, 80%[	=Max. 80%	All
Interest rate (over 6 months)	0.06	0.06	0.06	0.06
Price increase (rate)	0.03	0.03	0.03	0.03
Unit value of bags (CFA francs)	10,143	10,143	10,143	10,143
Storage costs (unit cost over 6 months)	600	600	600	600
Number of bags stored	6	19	14	14
Loan rate	0.00	0.43	0.80	0.60
Net gain from warrantage				
Gain from storage	1,826	5,782	4,260	4,260
Storage cost	3,600	11,400	8,400	8,400
Reimbursement of loan	0	5,098	6,989	5,242
Net gain	−1,774	−8,231	−7,721	−6,825
Net gain per bag	−296	−433	−551	−488
Net gain from storage at home at no cost				
Gain from storage	1,826	3,295	852	1,704
Storage cost	0	0	0	0
Net gain	1,826	5,782	4,260	4,260
Net gain per bag	304	304	304	304
Relative gain of warrantage (vs home)				
Total relative gain	−3,600	−14,012	−11,981	−11,086
Relative gain by bag	−600	−737	−856	−792

Note: This table compares the costs and returns of warrantage for maize in 2013. In 2013, the price of grain increased by 3%. The loan rate and the number of bags stored are mean values computed in each subgroup of participants, namely those who stored grain without taking a loan, those who stored grain and borrowed less than the maximum amount allowed for a loan, and those who stored grain and borrowed the maximum amount allowed for a loan. The value of a maize bag is the average price that was used in the seven warehouses to value the collateral at the time of the deposit. We calculate the net gain of warrantage by taking the added-value of grain stored in the warehouse after six months ("gain from storage"), minus the storage costs (100 F per bag and per month), minus the reimbursement of the loan, which includes the capital and the interest (about 1% per month). We calculate the net gain of storing the same quantity on farm at no cost.

29,700 F. We calculate the net gain of warrantage by taking the added-value of grain stored in the warehouse after six months (about 27,100 F), minus the storage costs (100 F per bag and per month, i.e., 6,000 F here), minus the reimbursement of the loan (about 2,800 F), which include the capital and the interest (about 1% per month).[21]

To get an idea of how much the average farmer is willing to pay to store his grain in the warehouse rather than at home, we calculate the net gain of storing the same quantity on farm at no cost. We obtain a net gain of storing at home at no cost of about 27,100 F (or 260 F per bag), which means that on average that year, warrantage was a more profitable option. However, the same calculation by category of borrowing highlights that storing at home was more profitable than warrantage for those who did not take any credit since they recorded a loss of 2,160 F (or 600 F per bag).

In 2013 the story was different because the rise in grain prices was exceptionally low (only 3% on average). As a result, the capital gain was not enough to offset the cost of warrantage, as shown in table 5. Thus, it would have been more profitable not to use the warehouse and to sell grain to invest instead of using a loan. The average farmer who stored 14 bags of maize in the warehouse indeed recorded a loss of 11,000 F (or 800 F per bag). Figure 4 plots the cost of warrantage relative to storing at home at no cost for each participant, showing that a number of farmers are willing to participate into the scheme even if it may be quite costly. The demand for commitment provides a rationale for this behavior.

Hypothetical Risk and Time Preference Data

Here we describe the risk and time preference data that were collected during the baseline survey. We describe the design and procedure of the experiments and explain how we estimated the individual risk and time preferences from the experimental

[21] Inflation was very low over this period: 0.53% in 2013, −0.26% in 2014, and 0.95% in 2015 according to the World Bank. We thus ignored it in the calculation.

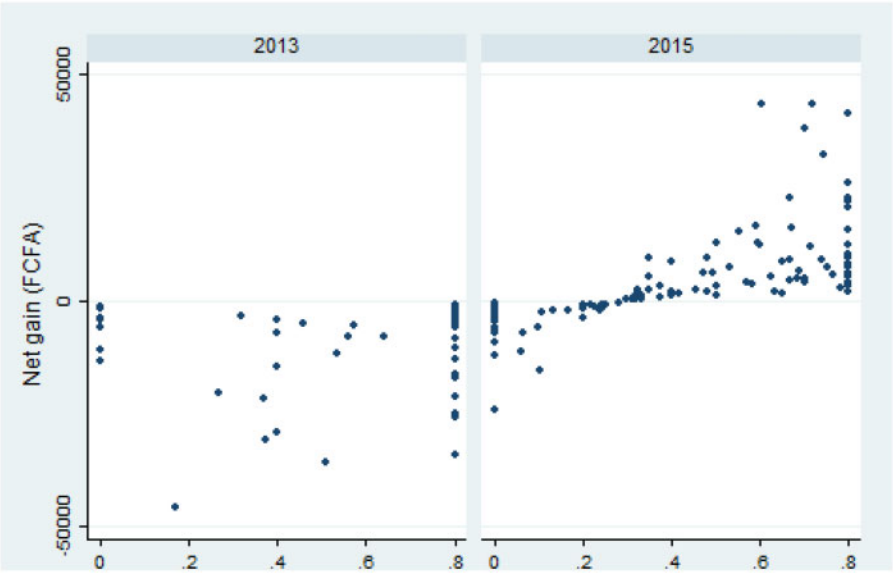


Figure 4. Net gain of warrantage versus storing at home in the sample

Note: This graph plots the net gain of warrantage versus storing at home, as calculated in tables 4 and 5. The horizontal axis represents the loan rate, that is the value of the loan divided by the value of grain stored in the warehouse at the time of the deposit. The price increase was 3% in 2013 and 25% in 2015.

results. It is important to mention that we make use of hypothetical surveys instead of incentivized scoring rules, not only because it is cheaper and easier to administer to large samples, but also because we wished to avoid disturbing the operations of other activities run by the same project. In particular, running incentivized games in seven CPF villages could have caused frustration in other CPF villages that were not included in the sample used for the inventory credit study.

Risk Preferences

This section presents the estimation of the risk aversion parameter.

Design and procedure of experiments

Our experiments were built on the risk aversion experiments developed by Holt and Laury (2002). We used a multiple price list design to measure individual risk preferences. We ran two experiments offering progressively lower and higher payoffs. In each experiment, participants were presented with a choice between two lotteries of risky and safe options, and this choice was repeated nine times with different pairs of lotteries, as illustrated in online supplementary table S1. Farmers were asked to choose either lottery A or lottery B. For example, the first row of online supplementary table S1 indicates that lottery A offers a 10% probability of receiving 1,000 CFA francs and a 90% probability of receiving 800 CFA francs, while lottery B offers a 10% probability of a 1,925 CFA francs payoff and a 90% probability of 50 CFA francs payoff.

The low payoff amounts were chosen because they were in line with the ranges of relative risk aversion parameters in previous experiments by Holt and Laury (2002) and Andersen et al. (2008), and because they amount to approximately one day's worth of income for a non-skilled worker in Burkina Faso (around 1,000 CFA francs per day, i.e., about $2 per day in 2012), which seemed credible to respondents. In the second experiment, farmers were asked to choose between lotteries with payoffs that were 10 times higher (10,000 CFA francs, or around $20, which corresponds to the average price of a 100 kg bag of maize during the harvest season).

In practice, lotteries A and B were represented by two bags of 10 marbles of different colours: green for 1,000 CFA francs, blue for 800 CFA francs, black for 1,925 CFA francs and transparent for 50 CFA francs.[22] The composition of the bags was made known to

[22] We conducted specific training sessions for the surveyors and equipped them with a material enabling them to explain the experimental games to farmers in a concrete way in order to facilitate their understanding of the game.

Table 6. Risk and Time Preferences: Summary Statistics

	Obs.	Mean	Std. Dev.	Quantiles 0.25	0.5	0.75
Risk aversion (r)	653	0.292	1.095	−0.358	0.545	1.370
Time discount rate (ρ)	653	0.068	0.187	−0.010	0.022	0.060
Hyperbolic parameter (h)	653	−1.029	0.108	−1.040	−1.005	−0.984

Note: This table displays detailed statistics for elicited measures of risk aversion and time discounting. The time discount rate is expressed in percentage per each four day. The hyperbolic parameter equals (minus) the ratio of the four-day delay discount factor and the one-month delay discount factor (converted to the equivalent discount factor for a four-day delay).

the farmers, but they could not see inside the bags. As indicated in the last column of online supplementary table S1, risk-neutral individuals ($r=0$) are expected to switch from lottery A to lottery B at row 5, risk loving individuals ($r<0$) are expected to switch to lottery B before row 5, and risk averse individuals ($r>0$) are expected to switch to lottery B after row 5.

Analysis of game results

In order to render our results comparable to previous studies, we assume a constant relative risk aversion (CRRA) utility function, which enables us to compute the intervals provided in the last column of online supplementary table S1. The CRRA utility function has the following form: $U(x) = x^{1-r_i}/(1-r_i)$, where x is the lottery prize and r_i, which denotes the constant relative risk aversion of the individual, is the parameter to be estimated. Expected utility is the probability weighted utility of each outcome in each row. An individual is indifferent between lottery A, with associated probability p of winning a and probability $1-p$ of winning b, and lottery B, with probability p of winning c and probability $1-p$ of winning d, if and only if the two expected utility levels are equal:

$$p.U(a) + (1-p).U(b) = p.U(c) + (1-p).U(d),$$

or

$$p.\frac{a^{1-r_i}}{1-r_i} + (1-p).\frac{b^{1-r_i}}{1-r} = p.\frac{c^{1-r_i}}{1-r_i} + (1-p).\frac{d^{1-r_i}}{1-r_i}$$

which can be solved numerically in terms of r_i.

We estimate risk aversion measures from these data in the following way. First, we compute the midpoint of the intervals for the low payoff and the high payoff experiments.[23] We then take the average of the two interval midpoints as a measure of risk aversion. This averaging has the advantage of reducing measurement error compared to approaches based on a single experimental measure (Falk et al. 2016). We find that most farmers are risk averse, with an average of $r=0.29$ (see table 6). This average value is lower than those obtained by Harrison, Humphrey, and Verschoor (2010), who conducted similar experiments in India, Ethiopia, and Uganda.

Time Preferences

This section presents the estimation of the time-discounting parameter.

Design and procedure of experiments

We elicit the individual time-discounting parameters following Andersen et al. (2008), who incorporate measures of risk aversion into the utility function curvature, which Andreoni, Kuhn, and Sprenger (2015) refer to as the double multiple price list (DMPL) method since it relies on one multiple price list for time and one for risk.[24] We built two time preference experiments in the spirit of Harrison, Lau, and Williams (2002) and Coller and Williams (1999). However, we had to adapt the content of the experiment in order to offer hypothetical pay-offs that were plausible to respondents. The two experiments differed in the time delays offered. Our design thus differs from previous studies, such as Bauer, Chytilova, and Morduch

[23] We take the upper bound for the first interval and the lower bound for the last interval.

[24] Andreoni, Kuhn, and Sprenger (2015) show that the convex time budgets (CTB) method, already used by Andreoni and Sprenger (2012), Augenblick, Niederle, and Sprenger (2015), and Giné et al. (2018), is a good alternative elicitation tool as it is likely to increase predictive power relative to DMPL estimates at the individual level (it makes predictions close to those of DMPL at the distributional level).

(2012) and Ashraf, Karlan, and Yin (2006), which include a binary variable indicating whether the time-discount rate elicited in the near future experiment is higher than in the distant future experiment.[25]

In the first experiment, farmers were invited to choose between receiving a given amount in one day's time (option A) or receiving a larger amount in five-days' time (option B), and this choice was repeated nine times, with increasing payoffs as option B. Online supplementary table S2 displays the experiment aiming to elicit the four-day discount rate. Note that we introduced a short delay in the current income option in the earlier time frame (1 day, i.e., tomorrow rather than today). This method should control for potential confounds due to lower credibility and higher transaction costs that may be associated with future payments (Harrison, Lau, and Williams 2002; Bauer, Chytilova, and Morduch 2012).

In the second experiment, farmers were invited to choose between receiving a given amount in one month's time (option A) or receiving a larger amount in two-months' time (option B), and this choice was repeated eight times, with increasing payoffs as option B. Online supplementary table S3 displays the experiment aiming to elicit the one-month discount rate.

Analysis of game results

In order to render our results comparable to other studies, we assume that farmers have additively time-separable preferences with a per-period CRRA utility function. The form of the utility function is still: $U(x) = x^{1-r_i}/(1-r_i)$, where x is the lottery prize and r_i denotes the constant relative risk aversion of the individual. An agent is indifferent between receiving payment M_t at time t or payment M_{t+1} at time $t+1$ if and only if

$$U(w+M_t) + \frac{1}{1+\rho_i}U(w) = U(w) + \frac{1}{1+\rho_i}U(w+M_{t+1})$$

where w is his background consumption and ρ_i accounts for the discount rate. Using the CRRA per-period utility function and assuming no background consumption ($w=0$), we write:

$$\frac{M_t^{1-r_i}}{1-r_i} = \frac{1}{1+\rho_i}\frac{M_{t+1}^{1-r_i}}{1-r_i},$$

from which we can explicitly solve for ρ_i as a function of risk aversion r_i:

$$\rho_i = \left[\frac{M_{t+1}}{M_t}\right]^{1-r_i} - 1.$$

We use the previously estimated risk aversion parameters (r_i) to calculate the interval bounds. We then compute interval midpoints for the two-time preference experiments, and take the average of these two midpoints as our estimate of an individual's discount rate.[26] We find that farmers are very impatient on average, with an average discount rate of 7% for a four-day period, that is, 66% per month (see table 6).

Our estimates of the time preference parameter fall well above previous discount rate estimates among selected populations in developed countries, which range between 1% and 3% per month (Harrison, Lau, and Williams 2002). Our estimates also suggest that the farmers in our sample have higher discount rates than the rural villagers who participated in the experiments conducted by Tanaka, Camerer, and Nguyen (2010) in Vietnam and Bauer, Chytilova, and Morduch (2012) in India. Our discount rate estimates also differ from those provided by Liebenehm and Waibel (2014), who conducted similar experiments with 211 households in Mali and Burkina Faso in 2007 and

[25] Our design does not allow us to construct such a binary variable since the two experiments that we used differed in the time delays offered (subjects were given the opportunity to wait five days in the first experiment and one month in the second experiment, and the rewards in the two experiments were not equivalent). We acknowledge that this prevents us from directly comparing our measurements to those of Bauer, Chytilova, and Morduch (2012) and Ashraf, Karlan, and Yin (2006), but it is a trade-off that we were obliged to make in order to construct a time experiment that made sense to participants. We ran a pilot study with several volunteer farmers, who were asked the same questions as in Andersen et al. (2008), where respondents are offered a choice between option A in one month and option B in seven months. All of the respondents in the pilot preferred to receive the small amount in one month, rather than the greater amount in seven months, no matter how big the greater amount was. We thus had to adapt the far-future experiment in order to offer farmers a more plausible tradeoff, which led us to build an experiment based on a delay of one month. We constructed the near-future experiment in an equally ad hoc manner. Trial and error led us to build the near-future experiment using a four-day delay.

[26] In order to render the two time-discounting measures comparable, we converted the one-month discount rate to the equivalent discount rate for a four-day delay.

2011. These authors report discount rates close to zero, meaning that surveyed households are extremely patient. However, they use a different experiment design (the respondents are offered a choice between immediate vs. future rewards) and a different estimation procedure (including a noise parameter), which may have led to lower discount rate estimates.

From the two elicited measures of impatience, we are then able to identify farmers who exhibit hyperbolic preferences. To construct a measure of hyperbolic discounting in accordance with the theory, we compute a measure of hyperbolic preferences which equals (minus) the ratio of the four-day delay discount factor and the one-month delay discount factor (converted to the equivalent discount factor for a four-day delay):

$$h_i = -\frac{1/(1+\rho_{\text{near}})}{1/(1+\rho_{\text{far}})}$$

where $1/(1+\rho_{\text{near}})$ (respectively, $1/(1+\rho_{\text{far}})$) refers to the four-day delay discount factor (respectively, one-month delay discount factor). A parameter h_i greater than –1 indicates that the farmer is more impatient in the near-future compared to a more distant future. The higher this parameter is, the stronger the hyperbolicity is.

We find that a large number of participants exhibit hyperbolic time preferences, and we obtain an average hyperbolic parameter of –1.03 (see table 6) and a median value of –1.005, which indicates that almost half of the sample exhibits hyperbolic preferences. This result is in line with recent literature that demonstrates the existence of hyperbolic discounting based on experimental data (Ashraf, Karlan, and Yin 2006; Giné et al. 2018).

Linking Preferences to Warehouse Inventory Credit Adoption

This section provides an empirical framework to test the prediction that the optimal quantity of grain w^* increases with the hyperbolic preference parameter h. We first present the empirical model that relates warrantage adoption to risk and time preferences. We then present the main results and the robustness checks.

Econometric Framework

We estimate an empirical model where farmer i's decision to engage in the system is a function of her discount rate ρ_i, level of risk aversion r_i, level of hyperbolic discounting h_i, other observable individual characteristics X_i, and village-by-year fixed effects:

$$(8) \quad W_{it} = f(\rho_i, r_i, h_i, X_i, \eta_{tv}, \epsilon_{it})$$

where η_{tv} is a vector of village-by-year dummies and ϵ_{it} is the individual error term.

Following de Janvry and Sadoulet (2006), we selected control variables X with the aim of controlling for household-specific features that affect production choices and hence the amount of harvest available to a farmer at the time when he makes his allocation decision (which we denote H in the theoretical model). Aside from risk and time preferences, both empirical models thus include a large set of farmer characteristics from the baseline survey, which include age and sex of the household's head, whether he received a formal education or not, the total land area (in hectares), the number of cattle, plows, and poultry, as well as the size of the labor force (measured as the number of family members who are employed in farming activities). The village-by-year dummies control for all other factors that appear in the theoretical model: the rate of return for doing something other than warrantage (which we denote as $(1+\Delta)$ in the theoretical model), the rate of return provided by warrantage $((1-\sigma)(1+\Delta))$, and the interest rate of the loan (i).

We first estimate a probit regression in which the dependent variable, W_{it}, takes on the value one if the farmer stored grain in the warehouse in year t (with or without a loan), and takes on the value zero otherwise:

$$(9) \quad \Pr(W_{it} = 1|\rho_i, r_i, h_i, X_i) = \Pr(\lambda_0 + \lambda_1\rho_i + \lambda_2 r_i + \lambda_3 h_i + X_i'\alpha_1 + \eta_{tv}'\alpha_2 + \epsilon_{it} > 0).$$

The degree of hyperbolic discounting, h_i, is the hyperbolic parameter. A positive coefficient λ_3 should then be interpreted as evidence that the more farmers exhibit hyperbolic time preferences, the more they use inventory credit.

We compute robust standard errors in a standard way. To test the extent to which our results are robust to cluster-corrected

standard errors, we provide the p-values calculated by using the score bootstrap method after clustering standard errors at the village level (Kline and Santos 2012).[27] We also fit a tobit model where the left-censored dependent variable W_i is the fraction of harvest stored in the warehouse (with or without a loan). Given that 2013 was the first year in which the warrantage system was implemented and 2015 was the third year, the results for the two years may differ. In what follows, we thus report estimates for 2013 and 2015 separately, as well as estimates based on both years together.

Results

Table 7 displays the results of a probit model that links individual preferences and participation in a warrantage program. Overall, the results appear very stable. We do not find evidence that risk aversion and time discounting affect the probability of engaging in the warrantage system at standard levels of significance (column 1). We do, however, find a significant and positive correlation between hyperbolic preferences and participation (column 2). In order to examine the extent to which this correlation may differ across years, we include an interaction term (hyperbolic parameter times year 2015) in the main model. We do not find any evidence of a stronger correlation in 2015 (column 3), and continue to find a positive correlation between hyperbolic preferences and participation when we estimate the model using 2013 data only (column 4) and 2015 data only (column 5). Taking our main result (as displayed in column 2), we calculate that a one standard deviation increase in the hyperbolic parameter is associated with a 21% increase in the probability of participating in warrantage. These results suggest that hyperbolic preferences may be a driver of the adoption of the warrantage system and that this effect remains stable in subsequent years.

Next, we investigate whether risk and time preferences may be related to the quantity that the farmer chooses to store in the warehouse. Table 8 displays the results of a tobit model, in which the dependent variable is the fraction of the total harvest that is stored in the warehouse. We do not find any evidence of a link between risk aversion or time discounting and quantity stored (column 1). In contrast, the correlation with the hyperbolic parameter is positive and significant (column 2). Here again, the size of the coefficient seems stable across time (column 3), and the correlation holds when considering 2013 alone (column 4). The coefficient is of a similar size but weakly significant (the p-value is 0.11) when considering 2015 alone (column 5).

We check whether our findings are driven by the small number of farmers who store grain in a warehouse without taking up a loan. To do so, we re-estimate the same probit model excluding those farmers and find that previous results hold, which suggest that hyperbolic preferences may be a driver of warrantage adoption even among those who ask for a loan (see online supplementary table S4).

In our sample, a fraction of farmers chose only lottery B for the entire payoff series (about 15% of players in the low payoff series, and up to 18% of players in the high payoff series chose this way), which would suggest that these farmers are extreme risk-lovers. One concern that arises with these results is that these farmers did not understand how the game worked, and incidentally drives our main result. Therefore, as a robustness check, we explicitly consider these risk lovers as a specific subset of the population. We augment our basic specification (table 7) with an interaction term between the hyperbolic preference parameter and a dummy that equals one if the farmer always chose the risky lottery (lottery B) in the two risk experiments (13% of the farmers behave this way). Our main results still hold (see online supplementary table S5).

Finally, we check the robustness of the main results by including binary variables for the quintiles of the variables of interest (r, ρ, and h) instead of continuous variables. We provide the results in online supplementary tables S6 and S7; they reveal that the results are driven by the very high levels of time discounting.

Alternative Explanations

Here we discuss alternative explanations for our results. In particular, we discuss whether individual income shocks or social pressure may explain our results. In each case, we

[27] The score bootstrap developed by Kline and Santos (2012) is an adaptation of the wild bootstrap of Wu (1986) and Liu (1988) for estimators such as probit.

Table 7. Participation in Warrantage: Probit Regression

	(1)	(2)	(3)	(4)	(5)
Risk aversion (r)	0.000	−0.013	−0.013	0.015	−0.035
	(0.053)	(0.053)	(0.053)	(0.077)	(0.075)
	[0.997]	[0.685]	[0.685]	[0.790]	[0.472]
Time discounting (ρ)	−0.350	0.205	0.195	0.319	0.138
	(0.321)	(0.384)	(0.386)	(0.588)	(0.509)
	[0.328]	[0.801]	[0.808]	[0.599]	[0.873]
Hyperbolic pref. (h)		1.769***	1.984**	1.971**	1.655**
		(0.633)	(0.907)	(1.016)	(0.802)
		[0.092]	[0.082]	[0.224]	[0.047]
Hyperbolic pref. x 2015			−0.013		
			(0.263)		
			[0.280]		
Village-by-Year FE	yes	yes	yes	yes	yes
Nb. obs.	1,149	1,149	1,149	653	496
Survey	2013 & 2015	2013 & 2015	2013 & 2015	2013	2015
Controls					
Plow	−0.020	−0.024	−0.024	−0.010	−0.039
	(0.045)	(0.046)	(0.046)	(0.066)	(0.063)
	[0.732]	[0.677]	[0.673]	[0.915]	[0.434]
Labor force	−0.022◇	−0.022◇	−0.022◇	−0.032◇	−0.012
	(0.014)	(0.014)	(0.014)	(0.021)	(0.019)
	[0.080]	[0.070]	[0.070]	[0.059]	[0.351]
Education	0.395***	0.408***	0.408***	0.432***	0.390***
	(0.099)	(0.100)	(0.100)	(0.145)	(0.139)
	[0.002]	[0.002]	[0.002]	[0.024]	[0.009]
Age	−0.006*	−0.006*	−0.006*	−0.006	−0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
	[0.189]	[0.187]	[0.187]	[0.353]	[0.141]
Sex	−0.034	−0.160	−0.160	0.142	−0.385
	(0.324)	(0.325)	(0.324)	(0.542)	(0.448)
	[0.955]	[0.845]	[0.851]	[0.787]	[0.673]
Total land area	0.071***	0.071***	0.072***	0.072***	0.072***
	(0.012)	(0.012)	(0.012)	(0.016)	(0.017)
	[0.001]	[0.001]	[0.001]	[0.007]	[0.009]
Cattle (less than 10)	0.422***	0.439***	0.440***	0.510***	0.398***
	(0.141)	(0.142)	(0.142)	(0.209)	(0.195)
	[0.066]	[0.059]	[0.059]	[0.046]	[0.065]
Cattle (more than 10)	0.252	0.279	0.279	0.484◇	0.099
	(0.223)	(0.224)	(0.224)	(0.316)	(0.314)
	[0.557]	[0.505]	[0.499]	[0.367]	[0.775]
Poultry	0.001	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
	[0.876]	[0.862]	[0.863]	[0.793]	[0.988]

Note: This table displays probit regressions where the dependent variable is a dummy variable that equals one if the farmers participated in the warrantage system, and zero elsewhere. Superscripts ***, **, *, and ◇) denote rejection of the null hypothesis of no impact at the 1%, 5%, 10%, and 15% significance levels, respectively. Robust standard errors are in parentheses. The coefficient and standard error of the interactive term in column (3) are computed as recommended in Ai and Norton (2003). The p-values were calculated by using the score method after clustering standard errors at the village level into brackets (Kline and Santos 2012).

provide arguments that make us confident that individual preferences are indeed linked to warrantage adoption.

Income Shocks

One could argue that our findings may arise due to an unobserved shock to income affecting both experimental measures of discounting and inventory credit adoption. Income shocks indeed have the potential to affect the way that farmers answer time-discounting questions, as well as their decisions to engage in inventory credit systems. If individuals are sufficiently liquidity-constrained, a negative shock such as a crop

Table 8. Quantity Stored as Collateral: Tobit Regression

	(1)	(2)	(3)	(4)	(5)
Risk aversion (r)	−0.014	−0.021	−0.021	0.007	−0.049
	(0.028)	(0.028)	(0.028)	(0.029)	(0.045)
Time discounting (ρ)	−0.242	0.063	0.053	0.132	−0.007
	(0.174)	(0.190)	(0.192)	(0.207)	(0.278)
Hyperbolic pref. (h)		0.986**	1.152**	0.862**	1.003◇
		(0.440)	(0.503)	(0.366)	(0.631)
Hyperbolic pref. x 2015			−0.292		
			(0.548)		
Village-by-Year FE	yes	yes	yes	yes	yes
Nb. obs.	1,138	1,138	1,138	653	485
Survey	2013 & 2015	2013 & 2015	2013 & 2015	2013	2015
Controls					
Plow	0.008	0.006	0.006	−0.001	0.009
	(0.024)	(0.024)	(0.024)	(0.024)	(0.037)
Labor force	−0.018*	−0.018*	−0.018*	−0.014*	−0.018
	(0.009)	(0.009)	(0.009)	(0.008)	(0.013)
Education	0.225**	0.232**	0.232**	0.162***	0.261*
	(0.098)	(0.100)	(0.100)	(0.053)	(0.154)
Age	−0.004*	−0.004*	−0.004*	−0.002*	−0.005◇
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Sex	−0.016	−0.092	−0.091	0.020	−0.210
	(0.177)	(0.184)	(0.182)	(0.230)	(0.263)
Total land area	0.037***	0.037***	0.037***	0.027***	0.040**
	(0.012)	(0.012)	(0.012)	(0.006)	(0.017)
Cattle (less than 10)	0.216***	0.222***	0.223***	0.189**	0.221*
	(0.083)	(0.083)	(0.083)	(0.080)	(0.118)
Cattle (more than 10)	0.164	0.177◇	0.178◇	0.190◇	0.119
	(0.115)	(0.116)	(0.116)	(0.118)	(0.177)
Poultry	−0.001	−0.001	−0.001	0.000	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)

Note: This table displays tobit regressions where the left-censored dependent variable is the fraction of harvest stored in the warehouse. Superscripts ***, **, *, and ◇) denote rejection of the null hypothesis of no impact at the 1%, 5%, 10%, and 15% significance levels, respectively. Robust standard errors appear in parentheses. The coefficient and standard error of the interactive term in column (3) are computed as recommended in Ai and Norton (2003).

failure due to reduced rainfall, for example, could cause them to respond as if they were more impatient now than in the future and simultaneously affect their savings behaviour. If this were the case, it is plausible that the correlation that we observe could be caused by these shocks rather than by a direct link between hyperbolic preferences and inventory credit adoption.

However, we argue that such an assumption is very unlikely to hold in our study due to the fact that a negative shock to income is likely to *increase* measures of hyperbolic preferences (Dean and Sautmann 2016) and *decrease* savings. On the contrary, our findings suggest the existence of a *positive* correlation between hyperbolic preferences and savings, which is in line with a demand for commitment.

One could also argue that most farmers who engaged in the inventory credit system chose to take a loan, which might indicate that they need cash, and this is presumably due to a negative shock to income. We believe that this interpretation is also unlikely to hold. First, farmers who are liquidity constrained have the option to sell their crops on the market (instead of taking a loan, which amounts to 80% of the value of their crop only). Second, it is challenging to identify an unobserved factor that would be likely to affect both the experimental measures of a farmer surveyed in January and the need for cash during the harvest season in November.

However, despite their improbability, we cannot definitively rule out the possibility that unobserved shocks to income could affect experimental measures of time-discounting and inventory credit adoption in more complex ways. We therefore design a robustness check to address this concern.

To do so, we exploit a new dataset that was collected in January 2016 from the sample of farmers who responded to the baseline survey. This follow-up survey provides the amount of maize, sorghum and millet harvested in October 2015 by participants and *non*-participants in warrantage in 2015. We include this variable as an additional control in the model of warrantage adoption. Because we do not have data on the 2013 harvest for farmers who did not participate in warrantage in 2013, we are able to perform this robustness test for the year 2015 only. We find that the link between time-inconsistency and warrantage adoption is robust to the inclusion of the harvest (see column 1 of online supplementary table S8). The correlation between time-inconsistency and quantity store remains of the same magnitude as before but lacks precision (see column 2 of online supplementary table S8).

Social Pressure

A final concern is that we inappropriately interpret our results as evidence that those farmers who engage in the inventory credit system are seeking a commitment savings device for its inherent benefits. As we point out at the beginning of the paper, there are a variety of reasons why farmers may opt to participate in warrantage. One of these reasons is that farmers who store their crops in warehouses are able to escape social pressure to share their harvest with kin and neighbors. Engaging in an inventory credit system may thus be an option for individuals seeking to escape this type of social pressure.

One could argue that our findings may arise due to an unobserved shock affecting both the way a farmer responds to time discounting questions and the standard of living of his neighbors. However, we include village-by-year fixed-effects in our model, which means that such covariant shocks are controlled for in our study.

Conclusion

Self-discipline problems may limit farmers' ability to save grain until the lean season, which may in turn hinder their capacity to ensure the food security of their household. In developing countries such as Burkina Faso, formal commitment savings devices are lacking. We argue that warrantage systems are likely to be effective commitment savings devices in this regard.

We partnered with a rural bank and a farmers organization in order to implement a warrantage system in seven villages in Burkina Faso, and we analyze the link between farmers' risk and time preferences and their likelihood to engage in the warrantage system. Our analysis is based on a series of hypothetical choice experiments in the field designed to elicit risk and time preferences before the beginning of the program, a baseline household survey, and two follow-up surveys carried out among participants in warrantage in the first and the third year of implementation. We found that farmers who exhibit stronger hyperbolic preferences are more likely to participate in the warrantage system than other, otherwise similar, farmers.

Inventory credit systems have been celebrated for giving farmers access to credit and, in doing so, providing them with an opportunity to overcome the "sell low buy high" phenomenon, notably because providing access to credit enables farmers to adjust their selling activities throughout the year and take advantage of seasonal price fluctuations. It is important to note that our findings do not discount the importance of the central feature of inventory credit systems, that is, the credit itself. Instead, we emphasize the features that are likely to motivate a farmer's decision to use such a system. Because the vast majority of farmers who entered the system chose to take out a loan, it appears that credit access serves as a strong motivation for engaging in the inventory credit system. The evidence we present here suggests that another explanation for the growing popularity of these systems may rest in their role in helping farmers to overcome their self-discipline problems.

Moreover, the results of our theoretical model suggest that there may be a variety of farmer responses to warrantage programs. Despite rising prices during the lean season, some farmers may not wish to store their grain in a certified warehouse over a six-month period. Specifically, these are farmers who are either not (or only slightly) inconsistent in their temporal preferences, or not sophisticated enough to realize that they are actually time-inconsistent and are too risk averse to take credit, as well as those who are too impatient to save their grain.

The warrantage system that was implemented in 2013 continues to function today. It should be noted, however, that the

long-term on-the-ground presence of the project proponent—the CPF—and the trust that characterized the relationship between farmers, the CPF and the rural bank in the study areas probably contributed to such encouraging results. In a less favorable context, many households may have been reluctant to entrust their grain to a farmer organization. It must also be recognized that the efficiency of the system can be significantly reduced when the state intervenes in the marketplace via price stabilization, as occurred in 2013. Finally, beyond the participation rate, the success of the system should also be measured through its impact on households' standards of living and food security. More work needs to be done in order to quantify these effects.

Supplementary Material

Supplementary material is available at *American Journal of Agricultural Economics* online.

References

Ai, C., and E.C. Norton. 2003. Interaction Terms in Logit and Probit Models. *Economics Letters* 80 (1): 123–29.

Aliber, M. 2001. Rotating Savings and Credit Associations and the Pursuit of Self-Discipline: A Case Study in South Africa. *African Review of Money Finance and Banking* 51–73.

Ambec, S., and N. Treich. 2007. Roscas as Financial Agreements to Cope with Self-Control Problems. *Journal of Development Economics* 82 (1): 120–37.

Andersen, S., G.W. Harrison, M.I. Lau, and E.E. Rutstrom. 2008. Eliciting Risk and Time Preferences. *Econometrica* 76 (3): 583–618.

Anderson, S., and J.M. Baland. 2002. The Economics of Roscas and Intrahousehold Resource Allocation. *Quarterly Journal of Economics* 117 (3): 963–95.

Andreoni, J., M.A. Kuhn, and C. Sprenger. 2015. Measuring Time Preferences: A Comparison of Experimental Methods. *Journal of Economic Behavior & Organization* 116: 451–64.

Andreoni, J., and C. Sprenger. 2012. Risk Preferences are Not Time Preferences. *American Economic Review* 102 (7): 3357–76.

Ashraf, N., D. Karlan, and W. Yin. 2006. Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines. *Quarterly Journal of Economics* 121 (2): 635–72.

Augenblick, N., M. Niederle, and C. Sprenger. 2015. Working Over Time: Dynamic Inconsistency in Real Effort Tasks. *Quarterly Journal of Economics* 130 (3): 1067–115.

Baland, J.M., C. Guirkinger, and C. Mali. 2011. Pretending to be Poor: Borrowing to Escape Forced Solidarity in Cameroon. *Economic Development and Cultural Change* 60 (1): 1–16.

Banerjee, A., and S. Mullainathan. 2010. The Shape of Temptation: Implications for the Economic Lives of the Poor. NBER Working Papers No. 15973, National Bureau of Economic Research.

Barr, A., and G. Genicot. 2008. Risk Sharing, Commitment, and Information: An Experimental Analysis. *Journal of the European Economic Association* 6 (6): 1151–85.

Basu, K. 2011. Hyperbolic Discounting and the Sustainability of Rotational Savings Arrangements. *American Economic Journal: Microeconomics* 3: 143–71.

Basu, K., and M. Wong. 2015. Evaluating Seasonal Food Storage and Credit Programs in East Indonesia. *Journal of Development Economics* 115: 200–16.

Bauer, M., J. Chytilova, and J. Morduch. 2012. Behavioral Foundations of Microcredit: Experimental and Survey Evidence from Rural India. *American Economic Review* 102 (2): 1118–39.

Bernheim, B.D., D. Ray, and S. Yeltekin. 2015. Poverty and Self-Control. *Econometrica* 83 (5): 1877–911.

Bester, H. 1987. The Role of Collateral in Credit Markets with Imperfect Information. *European Economic Review* 31 (4): 887–99.

Bryan, G., D. Karlan, and S. Nelson. 2010. Commitment Devices. *Annual Review of Economics* 2 (1): 671–98.

Burke, M., L.F. Bergquist, and E. Miguel. 2018. Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets. Working Paper No. 24476, National Bureau of Economic Research, Cambridge, MA, April.

Casaburi, L., and J. Willis. 2016. Time vs. State in Insurance: Experimental Evidence from Contract Farming in Kenya. Working Paper, American Economic Review.

Coller, M., and M. Williams. 1999. Eliciting Individual Discount Rates. *Experimental Economics* 2 (2): 107–27.

Coulter, J. 2009. Review of Warehouse Receipt System and Inventory Credit Initiatives in Eastern and Southern Africa. Report, UNCTAD Under the All ACP Agricultural Commodities Programme (AAACP), Geneva.

Coulter, J., and G. Onumah. 2002. The Role of Warehouse Receipt Systems in Enhanced Commodity Marketing and Rural Livelihoods in Africa. *Food Policy* 27 (4): 319–37.

de Janvry, A., and E. Sadoulet. 2006. *Progress in the Modeling of Rural Households' Behavior Under Market Failures*, 155–81. Boston: Springer U.S.

Dean, M., and A. Sautmann. 2016. Credit Constraints and the Measurement of Time Preferences. Working Paper. Available at http://www.columbia.edu~md3405/Working_Paper_12.pdf

di Falco, S., and E. Bulte. 2011. A Dark Side of Social Capital? Kinship, Consumption, and Savings. *Journal of Development Studies* 47 (8): 1128–51.

Dillon, B. 2016. Selling Crops Early to Pay for School: A Large-Scale Natural Experiment in Malawi. Working Paper No. 2351, African Development Bank.

Falk, A., A. Beckery, T. Dohmenz, D. Huffman, and U. Sunde. 2016. The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences. Working Paper 9674, IZA.

Fink, G., B.K. Jack, and F. Masiye. 2014. Seasonal Credit Constraints and Agricultural Labor Supply: Evidence from Zambia. Working Paper No. 20218, National Bureau of Economic Research.

Frederick, S., G. Loewenstein, and T. O'Donoghue. 2002. Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature* 40 (2): 351–401.

Fudenberg, D., and D.K. Levine. 2006. A Dual-Self Model of Impulse Control. *American Economic Review* 96 (5): 1449–76.

Giné, X., J. Goldberg, D. Silverman, and D. Yang. 2018. Revising Commitments: Field Evidence on the Adjustment of Prior Choices. *Economic Journal* 128 (608): 159–88.

Goldberg, J. 2017. The Effect of Social Pressure on Expenditures in Malawi. *J. Econ. Behav. Organ*. 143: 173–185.

Gross, J., C. Guirkinger, and J. Platteau. 2017. Buy as You Need: Nutrition and Food Storage Imperfections. Working Paper No. 12264, Centre for Economic Policy Research, London.

Gugerty, M.K. 2007. You Can't Save Alone: Commitment in Rotating Savings and Credit Associations in Kenya. *Economic Development and Cultural Change* 55 (2): 251–82.

Gul, F., and W. Pesendorfer. 2001. Temptation and Self-Control. *Econometrica* 69 (6): 1403–35.

Harris, C., and D. Laibson. 2001. Dynamic Choices of Hyperbolic Consumers. *Econometrica* 69 (4): 935–57.

Harrison, G.W., S. Humphrey, and A. Verschoor. 2010. Choice Under Uncertainty: Evidence from Ethiopia, India and Uganda. *Economic Journal* 120 (543): 80–104.

Harrison, G.W., M.I. Lau, and M.B. Williams. 2002. Estimating Individual Discount Rates in Denmark: A Field Experiment. *American Economic Review* 92 (5): 1606–17.

Heckman, J.J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47 (1): 153–61.

Hoff, K., and J.E. Stiglitz. 1990. Introduction: Imperfect Information and Rural Credit Markets—Puzzles and Policy Perspectives. *World Bank Economic Review* 4 (3): 235–50.

Holt, C.A., and S.K. Laury. 2002. Risk Aversion and Incentive Effects. *American Economic Review* 92 (5): 1644–55.

Jakiela, P., and O. Ozier. 2016. Does Africa Need a Rotten Kin Theorem? Experimental Evidence from Village Economies. *Review of Economic Studies* 83 (1): 231–268.

Kazianga, H., and C. Udry. 2006. Consumption Smoothing? Livestock, Insurance and Drought in Rural Burkina Faso. *Journal of Development Economics* 79 (2): 413–46.

Kline, P., and A. Santos. 2012. A Score Based Approach to Wild Bootstrap Inference. *Journal of Econometric Methods* 1: 23–41.

Laibson, D. 1997. Golden Eggs and Hyperbolic Discounting. *Quarterly Journal of Economics* 112 (2): 443–78.

Liebenehm, S., and H. Waibel. 2014. Simultaneous Estimation of Risk and Time Preferences Among Small-Scale Cattle Farmers in West Africa. *American Journal of Agricultural Economics* 96 (5): 1420–38.

Liu, R.Y. 1988. Bootstrap Procedures Under Some Non-I.I.D. Models. *Annals of Statistics* 16 (4): 1696–708.

Meier, S., and C. Sprenger. 2010. Present-Biased Preferences and Credit Card Borrowing. *American Economic Journal: Applied Economics* 2: 193–210.

O'Donoghue, T., and M. Rabin. 1999. Doing it Now or Later. *American Economic Review* 89: 103–24.

Phelps, E.S., and R.A. Pollak. 1968. On Second-Best National Saving and Game-Equilibrium Growth. *Review of Economic Studies* 35 (2): 185–99.

Platteau, J.P. 2000. *Institutions, Social Norms and Economic Development*. Amsterdam: Harwood Academic Publishers.

Sprenger, C. 2015. Judging Experimental Evidence on Dynamic Inconsistency. *American Economic Review* 105 (5): 280–85.

Stephens, E.C., and C.B. Barrett. 2011. Incomplete Credit Markets and Commodity Marketing Behaviour. *Journal of Agricultural Economics* 62 (1): 1–24.

Tanaka, T.,. C.F. Camerer, and Q. Nguyen. 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100 (1): 557–71.

Wu, C.F.J. 1986. Jackknife, Bootstrap and Other Resampling Methods in Regression Analysis. *Annals of Statistics* 14 (4): 1261–95.

The Journal of Development Studies, 2018
Vol. 54, No. 11, 1991–2006, https://doi.org/10.1080/00220388.2017.1344645

Linking Risk Aversion, Time Preference and Fertiliser Use in Burkina Faso

TRISTAN LE COTTY*, ELODIE MAÎTRE D'HÔTEL**, RAPHAEL SOUBEYRAN† & JULIE SUBERVIE†

*Centre de Coopération Internationale en Recherche Agronomique pour le Développement (CIRAD) and Centre International de Recherche sur l'Environnement et le Développement (CIRED), Montpellier, France, **Centre de coopération internationale en recherche agronomique pour le développement (CIRAD) and Marchés, Organisations, Institutions et Stratégies d'Acteurs (MOISA), Montpellier cedex 5, France, †French National Institute for Agricultural Research (INRA) and Laboratoire Montpelliérain d'Economie Théorique et Appliquée (LAMETA), Montpellier, France

(Original version submitted September 2014; final version accepted June 2017)

ABSTRACT *This paper investigates whether Burkinabe maize farmers' fertiliser-use decisions are correlated with their risk and time preferences. We conducted a survey and a series of hypothetical experiments on a sample of 1500 farmers. We find that more patient farmers do use more fertiliser, but it is only because they plant more maize (a fertiliser-intensive crop) rather than because they use more fertiliser per hectare of maize planted. Conversely, we find no statistically significant link between risk aversion and fertiliser use. We use a simple two-period model, which suggests that risk aversion may indeed have an ambiguous effect on fertiliser use.*

1. Introduction

Many agricultural experts argue that low fertiliser use is a key reason for Africa's insufficient food production and food insecurity (Sanchez, 2002). In recent years, Asia underwent a green revolution, that is major gains in agricultural productivity explained by the use of fertilisers and other modern inputs, while agricultural yields and fertiliser use have remained very low in Africa (Evenson & Gollin, 2003; Morris, Kelly, Kopicki, & Byerlee, 2007). Yet, recent trials in Kenya and Burkina Faso suggest that, when fertiliser is used at the recommended dose, the yield increases it generates make it a profitable investment (Duflo, Kremer, & Robinson, 2008, 2011; Koussoube & Nauges, 2017).[1] Given these promising results, why some farmers still use small amounts of fertiliser on their land is particularly puzzling.

In the literature, there has been extensive discussion on the determinants of the adoption of technology in agriculture, focusing on missing or imperfect markets for credit, insurance and land (Binswanger & Sillers, 1983; Dercon & Christiaensen, 2011; Karlan, Osei, Osei-Akoto, & Udry, 2014), lack of knowledge and education (Foster & Rosenzweig, 1995; Lambrecht, Vanlauwe, Merckx, & Maertens, 2014), some behavioural constraints (Duflo et al., 2011), heterogeneous returns (Suri, 2011), and insecure property rights (Jacoby et al., 2002). While risk and time preferences have been

Correspondence Address: Julie Subervie, French National Institute for Agricultural Research (INRA) and Laboratoire Montpelliérain d'Economie Théorique et Appliquée (LAMETA), Campus INRA-SupAgro, 2 place Pierre Viala, 34060 Montpellier cedex 2, France. Email: julie.subervie@supagro.inra.fr
Supplementary Materials are available at https://doi.org/10.1080/00220388.2017.1344645

recognised as being theoretically linked to technology adoption,[2] empirical evidence for a link between farmers' risk preferences and technology adoption is much more scarce (Knight, Weir, & Woldehanna, 2003; Liu, 2013; Liu & Huang, 2013) and to our knowledge, there is no empirical evidence for a link between time preferences and technology adoption in the literature.[3]

This paper is one of the first to provide empirical evidence of the link between time preferences and farmers' decisions to use fertiliser. Yet attitudes toward future events are integral to farmer decision-making, as they determine crop and input choices, investments and adoption of new technologies, among other things (Duquette, Higgins, & Horowitz, 2012). In this paper, we focus on the fertiliser purchase decision of maize farmers. We study fertiliser use by maize farmers in two cotton-producing regions in Burkina Faso where access to fertiliser and extension services is easy, that is the limited fixed costs of buying or learning to use fertiliser are not likely to be a major obstacle to fertiliser use. In this area, farmers typically buy fertiliser in May-June for maize and harvest their grain six months later. In 2013, in partnership with the Confédération Paysanne du Faso, a nation-wide farmers organisation, we conducted a survey of farmers and a series of hypothetical experiments to estimate the individual risk and time preferences of a representative sample of 1500 maize farmers.

We elicit farmers' risk and time attitudes using risk and time experiments with hypothetical payments. We built our time preferences experiment on Holt and Laury (2002) and on Andersen, Harrison, Lau, and Rutstrom (2008). We built our time preference experiment on Harrison, Lau, and Williams (2002) and on Coller and Williams (1999), and we adapted the content in order to offer hypothetical payoffs that were realistic to respondents, using the average price of a 100 kg bag of cereal as a reference value. The time discounting questions included both short-term trade-offs and future trade-offs.

In this paper, we match these measures of farmers' risk aversion and time preferences with different measures of fertiliser use. We capture the relationship between risk and time preferences and fertiliser use in a linear regression specification, which includes a range of observable individual characteristics and village-level dummies.

We find that the farmers who exhibit lower discount rates – whether in the short- or the long-term – purchase larger amounts of fertiliser for maize, but it is only because they plant more maize, which is a fertiliser-intensive crop, rather than because they use more fertiliser per hectare of maize planted. We find that a one-standard-deviation decrease in the discount rate is associated with a 6.5 per cent increase in the total amount of fertiliser used. Conversely, we find no statistically significant link between risk aversion and fertiliser use. We moreover use our data to examine the relationship between farmers' time inconsistency and fertiliser use.[4] However, our results are not conclusive.

To provide an interpretation of the empirical results, we also present a simple expected utility two-period model of a risk-averse farmer who chooses whether to purchase fertiliser or not. In the model, the curvature of the instantaneous utility function captures both the farmer's risk aversion and his propensity to smooth consumption over time. The model shows that discounting time decreases fertiliser use, while risk aversion has an ambiguous effect on fertiliser use that depends on the farmer's discounting. Because fertiliser is a risk increasing technology, one might expect a negative relationship between risk aversion and fertiliser use.[5] However, the relationship between risk aversion and fertiliser use may be more complex than it seems. Indeed, the use of fertiliser requires an investment whose returns are delayed, which affects inter-temporal consumption arbitrage. Therefore, risk averse farmers may want to use more fertiliser today in order to increase their future consumption, compared to risk neutral farmers, who are less concerned with inter-temporal smoothing. Since inter-temporal smoothing depends on impatience, the effect of risk aversion on fertiliser use is likely to depend on impatience too. More specifically, if the farmer is sufficiently patient, he is willing to sacrifice some consumption during the planting season in order to increase his consumption in the harvest season. In this case, an increase in risk aversion would tend to moderate the drop in consumption in the planting season (in order to smooth consumption over time) by decreasing investment in fertiliser. On the contrary, if the farmer is sufficiently impatient, he purchases a limited amount of fertiliser to ensure high consumption in the planting season. In this case, an increase in risk aversion would lead the farmer to increase fertiliser use in the planting season to avoid too low consumption in the harvest

period. This simple two-period model suggests that risk aversion has two potential effects with the opposite sign on fertiliser use, which may explain why we do not find any statistically significant empirical evidence on the relationship between risk aversion and fertiliser use with our data.

The results are robust to controlling for a range of observable individual characteristics and village-level dummies. We cannot rule out, however, the possibility that the results arise from an unobserved factor affecting experimental measures of discounting as well as fertiliser use. We discuss this concern in the last section of the paper.

The rest of the paper is organised as follows. Section 2 provides some background information on maize production and fertiliser use in Burkina Faso and describes the survey and the data set. Section 3 describes the design and procedure of the risk and time experiments and a descriptive analysis of the risk and time preferences we elicited. Section 4 provides a description of the empirical framework and the results. Section 5 describes a stylised model of fertiliser use that provides intuition for our empirical results. We discuss causal inference in Section 6. Section 7 concludes the paper.

2. Survey data

2.1. Survey procedure

The survey design generated a representative sample of households in two administrative districts of Burkina Faso, the Tuy and Mouhoun provinces. These provinces are located in the western region of the country, which is the main maize production area. Data were collected in cooperation with the Confédération Paysanne du Faso (CPF), a nation-wide farmers organisation. A total of 73 villages were randomly selected from the CPF list (Figure 1). In these villages, an average of 20 households were selected through a door-to-door strategy with the aim of gathering a random sample of households. With the help of the Burkinabe Agriculture Ministry, 20 investigators and two supervisors were recruited for data collection. A total of 1502 households were surveyed in February 2013. The survey includes data on purchases of fertiliser and harvesting of the maize crop between January 2012 and January 2013. The surveys were conducted in the Dioula language. The investigators interviewed the household head, defined here as the person responsible for farming decisions.[6] The participants were interviewed face-to-face and participated in various hypothetical risk and time experiments.

2.2. Data description

Table 1 reports the mean values for the characteristics of the households. On average, surveyed households have 13 members, seven of whom work in farming activities. In almost all cases, the household head is a man with an average age of 43 years, who received a formal education in 40 per cent of cases and lives a 40-minute drive from the closest market.[7] The climate in the Tuy and Mouhoun provinces is characterised by adequate rainfall for maize cultivation (around 800 mm per year) and a marked dry season, which is suitable for maize and cotton production. Other main crops are sorghum and millet. On average, the households surveyed own 10 hectares of land of which they devote about two hectares to maize, three hectares to sorghum and millet, and about four hectares to cotton.

Farmers use hybrid maize seeds that have been optimised for specific traits, such as yield, and are more sensitive to fertiliser application than other crops.[8] Consequently, farmers apply fertiliser on their maize fields rather than on their sorghum and millet fields. This is consistent with some evidence from other African countries for higher rates of input use on maize plots, even compared to plots planted with cash crops (Sheahan & Barrett, 2014). This is also consistent with the relatively high maize yields we observe in our data: mean yields in our sample are 1.5 tons per hectare for maize and only 0.8 tons per hectare for sorghum and 0.7 tons per hectare for millet.[9] The farmers we surveyed purchased about 230 kg of N-P-K fertiliser[10] for maize in 2012, which corresponds to an average of 110 kg per hectare of maize. It is worth mentioning that these farmers also use fertiliser for cotton. However, they do not have to buy fertilisers for cotton in the planting season because they obtain fertilisers on a credit

Figure 1. Location of surveyed villages.

provided by the Societé Burkinabé des Fibres et des Textiles (SOFITEX), the Burkinabé semi-public cotton company.[11]

3. Hypothetical risk and time preference data

The farmers in the survey were asked questions concerning both risky and intertemporal choices. We used hypothetical questions rather than incentivised ones to elicit farmers' risk and time preferences for two main reasons. Aside from the obvious motivation for using hypothetical surveys instead of

Table 1. Sample characteristics

Characteristics	Unit	Obs.	Mean	Std. Dev.	Min.	Max.
Family size	number	1502	12.7	8.9	1	70
Labour force	number	1502	7.1	5.4	1	48
Sex	man = 1	1502	1.0	0.1	0	1
Age	year	1502	42.8	12.7	14	90
Education	yes = 1	1502	0.4	0.5	0	1
Province	Tuy = 1	1502	0.4	0.5	0	1
Cattle (none)	yes = 1	1502	0.2	0.4	0	1
Cattle (less than 10)	yes = 1	1502	0.6	0.5	0	1
Cattle (more than 10)	yes = 1	1502	0.2	0.4	0	1
Ploughs	number	1502	2.0	1.7	0	18
Poultry	number	1502	21.3	27.2	0	300
Distance to market	minutes	1497	40.1	25.4	0	122
Purchase of fertiliser for maize						
Total amount of NPK fertiliser	kg	1502	231.5	419.4	0	5800
NPK fertiliser intensity	kg/ha	1250	109.8	73.5	0	500
Cultivated areas						
Total	ha	1502	10.0	9.0	0	88.5
Maize	ha	1502	2.1	3.3	0	35
Sorghum	ha	1502	1.8	2.2	0	30
Millet	ha	1502	0.9	1.6	0	25
Cotton	ha	1502	4.0	4.6	0	45
Peanut	ha	1502	0.3	0.5	0	5.5
Rice	ha	1502	0.1	0.4	0	8
Production						
Maize	ton	1497	3687.4	7190.0	0	97,500
Sorghum	ton	1499	1342.9	1970.5	0	26,520
Millet	ton	1500	544.7	1006.6	0	14,400
Cotton	ton	1497	4488.3	11,018.1	0	272,160
Peanut	ton	1488	188.7	417.5	0	5232
Rice	ton	1497	190.3	767.2	0	17,280

Note: The table provides summary statistics for a set of variables. yes = 1 means the variable is a dummy, Tuy = 1 means that the province is the Tuy region when the variable equals 1 and the Mouhoun region when the variable equals 0.

incentivised scoring rules (that is it is cheaper and easier to administer to large samples), we also wished to avoid disturbing the operations of other activities run by the same project.[12]

3.1. Design and procedure of experiments

Risk choices. Our hypothetical questions were built on the risk aversion experiments conducted by Holt and Laury (2002). We designed a multiple price list to measure individual risk preferences. We ran two experiments offering successively low and high payoffs. In each experiment, each participant was presented a choice between two lotteries of risky and safe options, and the choice was repeated nine times with different pairs of lotteries, as illustrated in Table 2. Farmers were asked to choose either lottery A or lottery B. For example, the first row of Table 2 indicates that lottery A offers a 10 per cent probability of receiving 1000 CFA and a 90 per cent probability of receiving 800 CFA, while lottery B offers a 10 per cent probability of a 1925 CFA payoff and a 90 per cent probability of 50 CFA payoff.

Low payoffs were chosen because they were in line with the ranges of relative risk aversion parameters used in previous experiments by Holt and Laury (2002) and Andersen et al. (2008), and because they amount to approximately one day's income for a non-skilled worker in Burkina Faso (around 1000 CFA, that is about 2 USD a day in 2012), which seemed credible to respondents. In the

Table 2. The paired lottery-choice decisions with low payoffs

	lottery A				lottery B					
	p	gain a	$1-p$	gain b	p	gain c	$1-p$	gain d	range of r	
1	0.1	1000	0.9	800	0.1	1925	0.9	50	$-\infty$	−1.71
2	0.2	1000	0.8	800	0.2	1925	0.8	50	−1.71	−0.95
3	0.3	1000	0.7	800	0.3	1925	0.7	50	−0.95	−0.49
4	0.4	1000	0.6	800	0.4	1925	0.6	50	−0.49	−0.14
5	0.5	1000	0.5	800	0.5	1925	0.5	50	−0.14	0.15
6	0.6	1000	0.4	800	0.6	1925	0.4	50	0.15	0.41
7	0.7	1000	0.3	800	0.7	1925	0.3	50	0.41	0.68
8	0.8	1000	0.2	800	0.8	1925	0.2	50	0.68	0.97
9	0.9	1000	0.1	800	0.9	1925	0.1	50	0.97	1.37
10	1	1000	0	800	1	1925	0	50	1.37	$+\infty$

Note: The last column was not shown to the respondents. It provides the associated interval for the CRRA parameter using the CRRA utility specification. In lottery A, p is the probability to gain a and $1-p$ the probability to gain b. In lottery B, p is the probability to gain c and $1-p$ the probability to gain d.

Table 3. The paired lottery-choice decisions with high payoffs

	lottery A				lottery B					
	p	gain a	$1-p$	gain b	p	gain c	$1-p$	gain d	range of r	
1	0.1	10,000	0.9	8000	0.1	19,250	0.9	500	$-\infty$	−1.71
2	0.2	10,000	0.8	8000	0.2	19,250	0.8	500	−1.71	−0.95
3	0.3	10,000	0.7	8000	0.3	19,250	0.7	500	−0.95	−0.49
4	0.4	10,000	0.6	8000	0.4	19,250	0.6	500	−0.49	−0.14
5	0.5	10,000	0.5	8000	0.5	19,250	0.5	500	−0.14	0.15
6	0.6	10,000	0.4	8000	0.6	19,250	0.4	500	0.15	0.41
7	0.7	10,000	0.3	8000	0.7	19,250	0.3	500	0.41	0.68
8	0.8	10,000	0.2	8000	0.8	19,250	0.2	500	0.68	0.97
9	0.9	10,000	0.1	8000	0.9	19,250	0.1	500	0.97	1.37
10	1	10,000	0	8000	1	19,250	0	500	1.37	$+\infty$

Note: The last column was not shown to the respondents. It provides the associated interval for the CRRA parameter using the CRRA utility specification. p is the probability to gain a and $1-p$ the probability to gain b. In lottery B, p is the probability to gain c and $1-p$ the probability to gain d.

second experiment, farmers were asked to choose between lotteries with 10 times higher payoffs, 10,000 CFA (around 20 USD) corresponding to the average price of a 100-kg bag of cereal at harvest (Table 3).

In practice, lotteries A and B were materialised by two bags of 10 marbles of different colour: green for 1000 CFA, blue for 800 CFA, black for 1925 CFA and transparent for 50 CFA. The farmers were told what was in the bags, but they could not see the contents. Assuming a constant relative risk aversion (CRRA) utility function, we deduce that, as indicated in the last column of Table 2, risk neutral individuals ($r = 0$) are expected to switch from lottery A to lottery B at row five, risk loving individuals ($r < 0$) are expected to switch to lottery B before row five, and risk averse individuals ($r > 0$) are expected to switch to lottery B after row five.

Time choices. We based our time hypothetical questions on Harrison et al. (2002) and on Coller and Williams (1999), who collected experimental data in Denmark and in the United States, respectively. However, we had to adapt the content in order to offer hypothetical payoffs that made sense to the respondents. We conducted two experiments that differed in the time delays offered to respondents. In

Table 4. 'Would you prefer to get A in one day or B in five days?'

	A	B	range of δ	
1	10,000	10,400	0	0.016
2	10,000	10,700	0.016	0.027
3	10,000	11,000	0.027	0.039
4	10,000	11,500	0.039	0.057
5	10,000	12,000	0.057	0.076
6	10,000	13,000	0.076	0.111
7	10,000	14,000	0.111	0.144
8	10,000	17,000	0.144	0.236
9	10,000	20,000	0.236	0.320

Note: Column 'range of δ' indicates the associated interval for monthly discount rate δ for a respondent who switches from A to B. We use the CRRA utility specification and the expected utility model with constant discount factor.

Table 5. 'Would you prefer to get A in one month or B in two months?'

	A	B	range of δ	
1	10,000	12,000	0	0.06
2	10,000	15,000	0.06	0.13
3	10,000	18,000	0.13	0.19
4	10,000	20,000	0.19	0.23
5	10,000	23,000	0.23	0.28
6	10,000	29,000	0.28	0.38
7	10,000	48,000	0.38	0.60
8	10,000	75,000	0.60	0.83

Note: Column 'range of δ' indicates the associated interval for monthly discount rate δ for a respondent who switches from A to B. We use the CRRA utility specification and the expected utility model with constant discount factor.

the first experiment, farmers were invited to choose between receiving a given amount in one day's time (option A) or receiving a larger amount in five days' time (option B), and this choice was repeated nine times, with increasing payoffs, as option B. Table 4 shows the experiment aimed at eliciting the four-day delay discount rate. In the second experiment, farmers were invited to choose between receiving a given amount in one month's time (option A) or receiving a larger amount in two months' time (option B), and this choice was repeated eight times, with increasing payoffs as option B. Table 5 displays the experiment aiming to elicit the one month delay discount rate.

3.2. Estimation of risk and time parameters

In order to make our results comparable with those of previous studies, we assume a CRRA utility function of the following form:

$$U(w+x) = (w+x)^{1-r}/(1-r), \tag{1}$$

where w is the farmer's background consumption, x is the lottery prize and r is the parameter to be estimated and denotes the constant relative risk aversion of the individual. When the farmer faces a lottery with two outcomes a and b with corresponding probability p and $1-p$, we focus on his expected utility, which is given by $EU = pU(w+a) + (1-p)U(w+b)$.

We also assume that farmers have additively time separable preferences. An agent utility evaluated at time t from receiving payment g_t at time t and payment $g_{t+\Delta t}$ at time $t+\Delta t$ is given by:

$$U(w+g_t)+\rho(\Delta t)U(w+g_{t+\Delta t}) \tag{2}$$

where w is his background consumption, ρ accounts for the discount factor and Δt is the time interval between the two payments. We assume a constant discount rate, that is

$$\rho(\Delta t)=\left(\frac{1}{1+\delta}\right)^{\Delta t}, \tag{3}$$

where δ denotes the discount rate.

A common approach used to approximate the parameters consists of using the midpoints of intervals (see, for instance, Andreoni and Sprenger 2012). We use the intervals computed for each switching point in each experiment (see the last column in Tables 2–5). The approximation of the preference parameter is the midpoint of the interval corresponding to the row in which the farmer switched from choice A to choice B.[13]

3.3. Descriptive analysis of risk and time parameters

The upper part of Table 6 provides descriptive statistics for the different estimates of the risk aversion parameter. The results of the two experiments show that most farmers are risk averse. The low-payoff (resp. high-payoff) experiment showed that the average risk aversion parameter is $r = 0.37$ (resp. $r = 0.33$). These values are somewhat lower than those obtained by Harrison, Humphrey, and Verschoor (2010) who used similar experiments in India, Ethiopia, and Uganda. The lower part of Table 6 provides descriptive statistics for the estimates of the discount rate. In the one-month delay experiment, we find that the average discount rate is $\delta = 0.32$. In the four-day experiment, we find that the average time discount rate is $\delta = 0.10$. Overall, farmers thus appear to be very impatient with respect to the distant future, with an average value of 32 per cent per month. Interestingly, they are even more impatient with respect to the near future, with an average value of 10 per cent for each four-day interval. Our estimates of the time preference parameter are well above previous estimates of discount rates that have been elicited for selected segments of populations in developed countries, which range from 1 to 3 per cent per month (Harrison et al., 2002). Our estimates also suggest that the farmers in our sample have higher discount rates than rural villagers who participated in the experiments conducted by Tanaka, Camerer, and Nguyen (2010) in Vietnam and Bauer, Chytilova, and Morduch (2012) in India. Taken together, these results suggest that Burkinabe farmers are, on average, more impatient than Vietnamese and Indian farmers are, and that Vietnamese and Indian farmers are more impatient than a nationally representative sample of Danish people. This ranking makes sense since those with the least amount of wealth are expected to have the highest levels of impatience. Indeed, a very high discount rate characterises life among farmers in a developing country like Burkina Faso: life expectancy is relatively short, and the likelihood of losing one's savings due to diseases and agricultural shocks can be quite high.[14]

Finally, we follow Andersen et al. (2008) and Prelec (2004) in constructing a measure of present bias from the two time experiments available, assuming the following discount factor function[15]:

Table 6. Estimated risk and time preference parameters

Parameter	Obs.	Estimation	Mean	Std. Dev.
Risk aversion (low-payoffs)	1502	Midpoint	0.37	1.06
Risk aversion (high-payoffs)	1502	Midpoint	0.33	1.09
Discount rate (1-month)	1502	Midpoint	0.32	0.31
Discount rate (4-days)	1502	Midpoint	0.10	0.09

Note: This table provides summary statistics for the estimated risk and time preferences using various experiments.

Table 7. Estimated time preference parameter

Parameter	Obs.	Estimation	Mean	Std. Dev.
Discount rate (β, 1 month)	1502	Midpoint	0.25	0.22
Discount rate (β, 4 days)	1502	Midpoint	0.09	0.08
Decreasing impatience (−α)	1502	Midpoint	−0.57	0.40

Note: This table provides summary statistics for the estimated time preferences and the present bias parameter 'à la Prelec'.

$$\rho(\Delta t) = e^{-\beta(\Delta t)^{\alpha}}, \tag{4}$$

where β denotes the discount rate and $0 \leq \alpha \leq 1$ and $-\alpha$ is a measure of 'decreasing impatience'. The instantaneous discount rate implied by this discount factor function is $\alpha\beta(\Delta t)^{\alpha-1}$ and it collapses to β as α goes to 1. Using Equations (3) and (4) as well as the two interval midpoint values of δ (the one from the one-month delay experiment and the one from the four-day delay experiment), we compute β and α. We obtain an estimate for the time discounting parameter, β, and the present bias parameter,α. Table 7 provides descriptive statistics for the estimated discount rate when the farmers are assumed to have hyperbolic preferences. Most of the farmers have hyperbolic preferences, the average value of the hyperbolic preference parameter (α) is 0.57 and thus far below 1, meaning that farmers indeed have hyperbolic preferences.

4. Econometric framework and results

4.1. Econometric framework

We capture the relationship between risk and time preferences and fertiliser use in a linear regression specification, which includes a range of observable individual characteristics and village level dummies:

$$\text{Fertilizer Use}_i = a + \beta RiskPref_i + \gamma TimePref_i + \mathbf{C}'_{\mathbf{i}}\boldsymbol{\theta} + \eta_v + \varepsilon_i, \tag{5}$$

where Fertilizer Use_i is a measure of fertiliser use by farmer i, $RiskPref_i$ is a measure of farmer i's risk aversion, and $TimePref_i$ is a measure of farmer i's time preferences. C'_i is a set of farmer-specific control variables, which includes the total cultivated area, the number of ploughs, the number of cattle, the number of poultry, sex, age, education of the head of the household, labour force,[16] distance to the market and province. η_v is a village dummy.

Fertiliser use. We use three different measures of fertiliser use. The first variable, called *Intensity*, refers to the quantity of N-P-K fertiliser purchased to grow maize (in kg) per hectare of maize owned. The second variable, called *Fertiliser*, refers to the quantity of N-P-K fertiliser purchased to grow maize (in kg). The last measure, called *Maize Area*, refers to the area of land under maize (in hectares). Since we use the total cultivated area as a control variable, the effect of risk and time preferences on the area under maize actually captures the effect of these preferences on the share of land that is devoted to maize.

Risk and time preferences. We use the two risk parameters obtained from the low and the high payoff experiments as well as the time preference parameters obtained from the four day and the one month delay experiments.

Table 8. Fertiliser use intensity and risk and time preferences

	[1] Intensity (kg/ha)	[2] Intensity (kg/ha)	[3] Intensity (kg/ha)	[4] Intensity (kg/ha)
Risk aversion	1.72	3.43**	1.76	3.48**
	(1.91)	(1.71)	(7.9)	(1.73)
Discount rate	3.39	2.65	6.26	3.62
	(6.31)	(6.23)	(20.08)	(20.19)
Delay	1 month	1 month	4 days	4 days
Payoffs	low	high	low	high
Obs.	1250	1250	1250	1250

Note: Standard errors clustered at village level are in parentheses. significant at 10 per cent; significant at 5 per cent; significant at 1 per cent. All regressions include village dummies, total cultivated area, sex, age, education, labour force, province, number of ploughs, cattle and poultry.

4.2. Empirical Results

Fertiliser use intensity. Table 8 provides the estimates of the effects of risk aversion and time discounting on the intensity of fertiliser use (kg of NPK per hectare). Overall, we do not find any robust statistically significant link between risk aversion[17] or time discounting and the intensity of fertiliser use.

Total amount of fertiliser. Table 9 provides the estimates of the effects of risk aversion and time discounting on the total amount of N-P-K fertiliser purchased (in kg). Overall, the coefficient of time discounting is statistically significant and negative, whatever the regression model and the measure of time discounting used. A one standard deviation increase in the discount rate is associated with a 6.5 per cent decrease in the total amount of fertiliser purchased. Conversely, the coefficient of risk aversion remains not significant in all estimates.

Maize area. Table 10 provides the estimates of the effects of risk aversion and time discounting on the maize area. Overall, the results are qualitatively very similar to those previously obtained for the total amount of N-P-K fertiliser purchased. The coefficient of time discounting on maize area is negative and almost always statistically significant. A one standard deviation increase in the discount rate results is associated with a 5 per cent decrease on the area planted to maize. Conversely, the coefficient of risk aversion is not robustly significant.[18]

Table 9. Fertiliser use and risk and time preferences

	[1] Fertiliser (kg)	[2] Fertiliser (kg)	[3] Fertiliser (kg)	[4] Fertiliser (kg)
Risk aversion	4.25	5.86	4.72	6.21
	(5.29)	(5.29)	(5.22)	(5.38)
Discount rate	−47.56**	−48.11**	−155.58**	−157.24**
	(20.05)	(19.68)	(76.42)	(76.53)
Delay	1 month	1 month	4 days	4 days
Payoffs	low	high	low	high
Obs.	1502	1502	1502	1502

Note: Standard errors clustered at village level are in parentheses. significant at 10 per cent; significant at 5 per cent; significant at 1 per cent. All regressions include village dummies, total cultivated area, sex, age, education, labour force, province, number of ploughs, cattle and poultry.

Table 10. Maize area and risk and time preferences

	[1] Maize area (ha)	[2] Maize area (ha)	[3] Maize area (ha)	[4] Maize area (ha)
Risk aversion	0.04	0.02	0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Discount rate	−0.34*	−0.33**	−1.11**	−1.06**
	(0.15)	(0.15)	(0.52)	(0.52)
Delay	1 month	1 month	4 days	4 days
Payoffs	low	high	low	high
Obs.	1502	1502	1502	1502

Note: Standard errors clustered at village level are in parentheses. significant at 10 per cent; significant at 5 per cent; significant at 1 per cent. All regressions include village dummies, total cultivated area, sex, age, education, labour force, province, number of ploughs, cattle and poultry.

Table 11. Fertiliser use and hyperbolic preferences

	[1] Fertiliser (kg)	[2] Fertiliser (kg)	[3] Fertiliser (kg)	[4] Fertiliser (kg)
Risk aversion	5.12	6.55	4.75	6.25
	(5.18)	(5.33)	(5.22)	(5.38)
Discount rate	−71.24**	−71.93***	−182.32**	−184.92**
	(27.94)	(27.54)	(92.65)	(91.39)
−α (decreasing discount)	−20.89	−20.9	2.54	2.82
	(20.02)	(20.17)	(22.33)	(22.24)
Delay	1 month	1 month	4 days	4 days
Payoffs	low	high	low	high
Obs.	1502	1502	1502	1502

Note: Standard errors clustered at village level are in parentheses. significant at 10 per cent; significant at 5 per cent; significant at 1 per cent. All regressions include village dummies, total cultivated area, sex, age, education, labour force, province, number of ploughs, cattle and poultry.

Table 12. Maize area and hyperbolic preferences

	[1] Maize area	[2] Maize area	[3] Maize area	[4] Maize area
Risk aversion	0.05	0.02	0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Discount rate	−0.52**	−0.49**	−1.41**	−1.35**
	(0.21)	(0.21)	(0.67)	(0.68)
−α (decreasing discount)	−0.12	−0.11	0.05	0.05
	(0.12)	(0.12)	(0.14)	(0.14)
Delay	1 month	1 month	4 days	4 days
Payoffs	Low	high	low	high
Obs.	1502	1502	1502	1502

Note: Standard errors clustered at village level are in parentheses. significant at 10 per cent; significant at 5 per cent; significant at 1 per cent. All regressions include village dummies, total cultivated area, sex, age, education, labour force, province, number of ploughs, cattle and poultry.

Time-inconsistency. Table 11 (resp. Table 12) provides the estimated relationship between the measure of present bias ($-\alpha$) and the total amount of fertiliser used for maize (resp. maize area). Overall, the results are not conclusive. The coefficient of the present bias parameter does not appear to be stable and is not statistically significant in most estimates.

5. A simple model of fertiliser use

In this section, we develop a two-period stylised agricultural household model focusing on the role of risk and time preferences in determining fertiliser use.[19] The model provides the main intuitions behind the expected effects of the discount rate and of the risk aversion parameter on fertiliser use. Consider a two period model.[20] The first period refers to the planting season (subscript p) and the second to the harvest season (subscript h). A household's indirect utility depends on consumption of a generic good with price one. The household has initial wealth B_0 and faces an agricultural production technology, which is represented by a production function F. The quantity of fertiliser is denoted by x. The levels of inputs (such as land and labour) are given. Production is stochastic, that is F depends on a random variable, ξ, which represents unanticipated shocks on agricultural production (for example, weather shocks). At planting, the household can either consume its wealth, c_p, or purchase fertiliser. The price of fertiliser is normalised to one. At harvest, the household consumes its agricultural production, c_h. For the sake of simplicity, we assume the household has no savings.[21]

The household chooses the quantity of fertiliser that maximises its discounted utility. Its crop season optimisation problem can be expressed as follows:

$$\text{Maximize}_{c_p,c_h,x}\, EU = \frac{1}{1-r}\left(c_p\right)^{1-r} + \frac{1}{1+\delta}\frac{1}{1-r}E\left(\left(c_h\right)^{1-r}\right) \tag{6}$$

s.t.

$$c_p + x \leq B_0 \text{ (planting season budget constraint)}, \tag{7}$$

and,

$$c_h \leq F(x,\xi) \text{ (harvest season budget constraint)}. \tag{8}$$

Utility is assumed to be time separable with constant relative risk aversion parameter. Preferences are fully described by two parameters: r, which measures the relative risk aversion and δ, which refers to the discount rate. E denotes the expectation operator. The production function, F, is assumed to be (strictly) increasing and concave with respect to the quantity of fertiliser used, $F_x > 0$ and $F_{xx} \leq 0$.[22]

We solve the household's utility maximisation problem focusing on the optimal level of fertiliser use, x^* (proofs are relegated to Supplementary materials). We first show the following result:

Result 1 [Fertiliser use and impatience]: *The optimal quantity of fertiliser used always decreases with impatience*:

$$\frac{\partial x^*}{\partial \delta} < 0.$$

Patient households use more fertiliser than impatient households. This result is due to the time gap between the planting season and the harvest season.

Our second result focuses on the level of risk aversion of the household:

Result 2 [Fertiliser use and risk aversion]: *The optimal quantity of fertiliser used increases with risk aversion for sufficiently impatient households: there exists $\tilde{\delta} \geq 0$ such that*

$$\frac{\partial x^*}{\partial r} \geq 0 \Leftrightarrow \delta \geq \tilde{\delta}.$$

The intuition of Result 2 is as follows. If the household strongly discounts future utility, that is if $\delta \geq \tilde{\delta}$, it tends to choose a high level of consumption c_p and uses a small amount of fertiliser in the planting season. However, the more risk averse the household, the smaller its consumption in the

planting season because it seeks to smooth its consumption between the two seasons. To ensure sufficient consumption at harvest, it has to increase soil fertility by purchasing fertiliser. As a result, in that case, fertiliser use at the planting season increases with risk aversion. Conversely, if the household does not strongly discount future utility, that is $\delta \leq \tilde{\delta}$, it tends to use large quantities of fertiliser and chooses a low consumption level in the planting season. However, the more risk averse the household, the less it uses fertilisers in the planting season, again because it seeks to smooth its consumption. In order to increase its consumption in the planting season, it must use less fertiliser. For this reason, in that case, fertiliser use decreases with risk aversion.

In both cases, risk aversion acts as a countervailing power of farmers' time preference: risk aversion increases fertiliser use among impatient farmers and decreases fertiliser use among patient farmers. Whether risk aversion increases or decreases fertiliser use thus remains an empirical issue.

In this paper, we did not find any significant empirical link between risk aversion and fertiliser use. The results obtained from the model suggest that risk aversion can have either a positive or a negative effect on the total amount of fertiliser used for maize and on the proportion of land that is devoted to maize. This may explain why we did not find a robust empirical link between risk aversion and fertiliser used for maize and the share of land planted under maize.

6. Discussion

A concern with our findings is that they arise from an unobserved complementary input that affects both our experimental measures of discounting and fertiliser use.

The availability of complementary inputs, such as a labour force, can indeed affect the way farmers answer time-discounting questions as well as their decision to purchase and use fertiliser. A farmer in a household with a relatively high proportion of children or elderly family members is more likely to need cash, typically for health care, and consequently may seem to be impatient in the experiment. This farmer is also less likely to use fertiliser because he has less available labour force on the farm. In order to deal with this issue (albeit imperfectly), we include the labour force as a control in all the regression models used.

In the same line, we cannot exclude that our findings arise from unobserved soil quality[23] or rainfall shocks. Unfortunately, we do have good measures to control for these possible confounders. We believe that village dummies are likely to control for much of the effect of unobserved factors.[24]

7. Conclusion

We analysed the empirical link between individual risk and time preferences and the use of chemical fertilisers by maize farmers in Burkina Faso. We matched different measures of farmers' risk aversion and time preferences with different measures of fertiliser use. Our main result is that farmers who exhibit higher impatience devote a smaller proportion of their land to fertiliser-intensive crops – maize in our study – and purchase smaller amounts of fertiliser at planting. This suggests that time preferences may play an important role in fertiliser-use decisions.

This interpretation needs to be confirmed by studies that establish causal links. However, our findings may have important policy implications. They suggest that reducing the cost of fertiliser during the planting season could effectively foster agricultural productivity in Burkina Faso (Duflo et al., 2011) simply because this would push impatient farmers to purchase more fertiliser at planting. This could be achieved by fertiliser subsidies distributed in the form of vouchers. Alternatively, it could be achieved with a mechanism that provides fertiliser in kind to farmers during the planting season and recovers the cost of the fertilisers at harvest by deducting it from the farmers' sales, a mechanism that already exists in the cotton sector.

Acknowledgements

This research would not have been possible without the full cooperation of the Confédération Paysanne du Faso. Funding for this research was provided by the European Union with counterpart funding from AGRINATURA for the Farm Risk Management for Africa project, coordinated by CIRAD. We thank the participants in the CSAE Annual Conference on Economic Development in Africa and the Development Economics Seminar of the French National Institute for Agricultural Research for useful comments. All views expressed in this article are those of the authors alone. Data and codes are available upon request.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Directorate-General for Development and Cooperation - EuropeAid [2011/260-875].

Notes

1. Koussoubé & Nauges (2017) study the profitability of chemical fertilisers using large-scale plot data from Burkina Faso. They estimate maize yield response to nitrogen to be 19 kg/ha on average and to vary with soil characteristics. Profitability, which they measure through the calculation of a marginal value cost ratio, is estimated at 1.4, with significant variations across regions.
2. See, among others, Feder (1980), Feder, Just, and Zilberman (1985), Jacoby et al. (2002), Duflo et al. (2011), and Dercon and Christiaensen (2011).
3. Knight et al. (2003) analysed the adoption of technology by Ethiopian farmers. They established an empirical link between a measure of risk aversion and the adoption of innovation, a dichotomous variable that is set to one if farmers adopted at least one new input (fertiliser or pesticide) and one new crop. Liu (2013) examined the role of risk aversion in the decision to adopt genetically modified cotton in China and found that farmers who are more risk averse adopt genetically modified cotton later than farmers who are not. Conversely, Liu and Huang (2013) showed that risk aversion is positively correlated with pesticide use by Chinese farmers.
4. The results of a recent study in Kenya, Duflo et al. (2011) suggested that farmers may not purchase fertiliser because they tend to be present biased. This time-inconsistency would push them to procrastinate, postponing fertiliser purchases until later periods, when they may be too impatient to purchase fertiliser. Under this assumption, there may be a relationship between farmers' time inconsistency and fertiliser use.
5. It is worth-mentioning that the effect of risk aversion on the adoption of innovation depends on the risk increasing or risk decreasing nature of the innovation itself. For example, the use of pesticides provides protection against production uncertainty, which implies a risk decreasing effect (Feder, 1979). Conversely, the use of fertiliser increases yield variability, which implies a risk increasing effect (Just & Pope, 1979).
6. We remain agnostic concerning the way in which the individual preferences and beliefs are aggregated within each family.
7. We calculated the distance between each village and its associated assembly market using Arcgis software. We assumed the speed of vehicles traveling on paved roads to be 40 km per hour and the speed on unpaved roads to be 10 km per hour.
8. Yield increases thanks to nitrogen uptake are larger for maize than for sorghum and millet (Ciampitti, Balboa, Mahama, & Prasad, 2014).
9. National averages are 1.8 t/ha for maize, 1.1 t/ha for sorghum and 0.85 t/ha for millet according to the Food and Agriculture Organization of the United Nations (FAO).
10. N-P-K fertilisers are three-component fertilisers providing nitrogen, phosphorus, and potassium.
11. The farmers who use this credit in the planting season reimburse the price of fertiliser when the cotton is harvested and they are paid for their cotton production by SOFITEX.
12. Vieider et al. (2015) show that incentivised measures and survey measures can be highly correlated.
13. If the farmer always chose choice A, then the approximation of his parameter is the higher bound of the interval. If the farmer always chose choice B, then the approximation is the lower bound of the interval.
14. Our estimates of the discount rate also differ considerably from those provided by Liebenehm and Waibel (2014), who conducted similar experiments with 211 households in Mali and Burkina Faso in 2007 and 2011. These authors report

discount rates close to zero, meaning that households are extremely patient. This is a surprising result considering that poor people are usually expected to have high levels of impatience.

15. We also used Laibson's quasi-hyperbolic preferences (Laibson, 1997). This does not qualitatively affect any of our results.
16. Labour force is defined as the family members who are willing and able to work in the field.
17. Risk aversion increases the intensity of fertilisers used in two of the specifications that do correspond to high payoffs experiments used to elicit risk aversion parameters, but this effect is not robust to the specification that correspond to low payoffs experiments.
18. We also estimated econometric models that include an interaction term between risk aversion and time preference. We failed to reject the null hypothesis of no significance of this interaction term while our main results remained unchanged.
19. See Dercon and Christiaensen (2011) for a more general formulation of the dynamic decision problem.
20. An implication of the two period assumptions is that constant and hyperbolic time preferences are not distinguishable. This simplification is convenient, since we do not want to focus on hyperbolic preferences (as we find no evidence of a link between time inconsistency and fertiliser use).
21. Consequently, the only way to increase consumption at harvest is to purchase more fertiliser in the planting season. This is obviously a caricature of possible options, but the goal of the model is to provide a simple explanation for the role of risk aversion in the farmer's decision to buy fertiliser. Introducing the possibility of saving would not alter the qualitative results.
22. Fertilisers increase the supply of nutrients in the soil. When the nutrient content of soils increases, yields typically increase at a decreasing rate. However, with sufficiently high levels of nutrient supplies, yields reach a plateau. With even higher nutrient supplies, the concentration of nutrients becomes toxic and yields decrease (IFA, 1992). Our assumption that F is increasing and concave is a reasonable assumption for farmers who do not make excessive use of fertilisers.
23. Marenya and Barrett (2009) examine fertiliser use conditional on soil quality in rural Kenya and provide evidence that soil quality matters to fertiliser uptake using plot-level data on soil quality and plot age.
24. We expect the variation in rainfall and soil quality within villages to be lower than the variation in rainfall and soil quality across villages.

References

Andersen, S., Harrison, G. W., Lau, M. I., & Rutstrom, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, *76*(3), 583–618. doi:10.1111/j.1468-0262.2008.00848.x

Andreoni, J., & Sprenger, C. (2012). Estimating time preferences from convex budgets. *American Economic Review*, *102*(7), 3333–3356. doi:10.1257/aer.102.7.3333

Bauer, M., Chytilova, J., & Morduch, J. (2012). Behavioral foundations of microcredit: experimental and survey evidence from rural India. *American Economic Review*, *102*(2), 1118–1139. doi:10.1257/aer.102.2.1118

Binswanger, H. P., & Sillers, D. A. (1983). Risk aversion and credit constraints in farmers' decision-making: A reinterpretation. *Journal of Development Studies*, *20*, 5–21. doi:10.1080/00220388308421885

Ciampitti, I., Balboa, G., Mahama, G., & Prasad, P. V. (2014, November). *Nitrogen use efficiency and related plant N mechanisms in Corn & Sorghum*. Paper presented at the ASA-CASSA-SSSA Annual Meeting, Long Beach, California.

Coller, M., & Williams, M. (1999). Eliciting individual discount rates. *Experimental Economics*, *2*(2), 107–127. doi:10.1023/A:1009986005690

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, *96*(2), 159–173. doi:10.1016/j.jdeveco.2010.08.003

Duflo, E., Kremer, M., & Robinson, J. (2008). How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *American Economic Review*, *98*(2), 482–488. doi:10.1257/aer.98.2.482

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, *101*(6), 2350–2390. doi:10.1257/aer.101.6.2350

Duquette, E., Higgins, N., & Horowitz, J. (2012). Farmer discount rates: Experimental evidence. *American Journal of Agricultural Economics*, *94*(2), 451–456. doi:10.1093/ajae/aar067

Evenson, R. E., & Gollin, D. (2003). Assessing the impact of the green revolution, 1960 to 2000. *Science*, *300*(5620), 758–762. doi:10.1126/science.1078710

Feder, G. (1979). Pesticides, information, and pest management under uncertainty. *American Journal of Agricultural Economics*, *61*(1), 97–103. doi:10.2307/1239507

Feder, G. (1980). Farm size, risk aversion and the adoption of new technology under uncertainty. *Oxford Economic Papers*, *32*(2), 263–283. doi:10.1093/oxfordjournals.oep.a041479

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, *33*(2), 255–298. doi:10.1086/451461

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in Agriculture. *Journal of Political Economy*, *103*(6), 1176–1209. doi:10.1086/601447

Harrison, G., Humphrey, S., & Verschoor, A. (2010). Choice under uncertainty: Evidence from Ethiopia, India and Uganda. *Economic Journal*, *120*(543), 80–104. doi:10.1111/j.1468-0297.2009.02303.x

Harrison, G. W., Lau, M. I., & Williams, M. B. (2002). Estimating individual discount rates in Denmark: A field experiment. *American Economic Review*, *92*(5), 1606–1617. doi:10.1257/000282802762024674

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655. doi:10.1257/000282802762024700

IFA. (1992). *IFA world fertilizer manual*. International Fertilizer Industry Association. Ludwigshafen:BASF.

Jacoby, H. G., Guo, L., & Rozelle, S. (2002). Hazards of expropriation: Tenure insecurity and investment in rural China. *American Economic Review*, *92*(5), 1420-447. doi:10.1257/000282802762024575

Just, R. E., & Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, *61*(2), 276–284. doi:10.2307/1239732

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal Of Economics*, *129*(2), 597-652. doi: 10.1093/qje/qju002

Knight, J., Weir, S., & Woldehanna, T. (2003). The role of education in facilitating risk-taking and innovation in agriculture. *Journal of Development Studies*, *39*(6), 1–22. doi:10.1080/00220380312331293567

Koussoube, E., & Nauges, C. (2017). Returns to fertilizer use: Does it pay enough? Some new evidence from Sub-Saharan Africa. *European Review of Agricultural Economics*, *44*(2), 183–210.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, *112*(2), 443–478. doi:10.1162/003355397555253

Lambrecht, I., Vanlauwe, B., Merckx, R., & Maertens, M. (2014). Understanding the process of agricultural technology adoption: Mineral fertilizer in eastern DR congo. *World Development*, *59*, 132–146. doi:10.1016/j.worlddev.2014.01.024

Liebenehm, S., & Waibel, H. (2014). Simultaneous estimation of risk and time preferences among small-scale cattle farmers in West Africa. *American Journal of Agricultural Economics*, *96*(5), 1420–1438. doi:10.1093/ajae/aau056

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics*, *95*(4), 1386–1403. doi:10.1162/REST_a_00295

Liu, E. M., & Huang, J. (2013). Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics*, *103*(0), 202–215. doi:10.1016/j.jdeveco.2012.12.005

Marenya, P. P., & Barrett, C. B. (2009). Soil quality and fertilizer use rates among smallholder farmers in western Kenya. *Agricultural Economics*, *40*(5), 561–572. doi:10.1111/agec.2009.40.issue-5

Morris, M., Kelly, V. A., Kopicki, R. J., & Byerlee, D. (2007). *Fertilizer use in African Agriculture: Lessons learned and good practice guidelines*. Washington, DC: The World Bank.

Prelec, D. (2004). Decreasing impatience: A criterion for non-stationary time preference and "Hyperbolic" discounting. *Scandinavian Journal of Economics*, *106*(3), 511–532. doi:10.1111/j.0347-0520.2004.00375.x

Sanchez, P. A. (2002). Soil fertility and hunger in Africa. *Science*, *295*, 2019–2020. doi:10.1126/science.1065256

Sheahan, M., & Barrett, C. B. (2014). *Understanding the agricultural input landscape in Sub-Saharan Africa: Recent plot, household, and community-level evidence* (Policy Research Working Paper no. WPS7014). Washington, DC: World Bank Group.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, *79*(1), 159–209. doi:10.3982/ECTA7749

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Review*, *100*(1), 557–571. doi:10.1257/aer.100.1.557

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association*, *13*(3), 421–452. doi:10.1111/jeea.2015.13.issue-3

AGRICULTURAL ECONOMICS

Agricultural Economics 49 (2018) 71–82

Why does on-farm storage fail to mitigate price volatility?

Elodie Maître d'Hôtel*, Tristan Le Cotty

CIRAD, Paris, France

Received 30 March 2016; received in revised form 26 April 2017; accepted 10 May 2017

Abstract

We analyze the role of farm stock management on price volatility under liquidity constraints and heterogeneous price expectations. In commodity markets, speculative behaviors by stockholders tend to reduce price volatility, but this is not the case in certain agricultural markets, where speculation by farmers regarding decisions to sell or store grain is subject to liquidity constraints and heterogeneous price expectations. Like stockholders, most farmers sell grain if they expect a price drop in the near future, but unlike stockholders, they are not necessarily able to purchase grain if they expect a price increase in the next period. Heterogeneous price expectations can also lead to suboptimal storage decisions, further increasing price volatility. For these reasons, the storage management behavior of farmers often fails to mitigate price drops in the way that speculation by stockholders does. We merge historical data on maize prices and household storage collected in Burkina Faso in order to build a dynamic panel over the 2005–2012 period. We show that carryover from one season to the next is associated with unexpected price drops during the preceding lean season and that carryover is associated with more frequent unexpected price drops following the subsequent post-harvest season.

JEL classifications: Q11, Q12, Q13, Q18

Keywords: Storage; Price volatility; Anticipation errors; Maize; Africa

1. Introduction

In developing countries, decisions regarding farm storage are subject to certain constraints that impact price behaviors and this impact is inadequately described by existing commercial stock management theory. The standard relation between stocks and price volatility is described in the competitive storage model (Deaton and Laroque, 1992). Although several studies have relaxed the restrictive assumptions of this model, they have not done so in a way that describes the impact of farm storage and marketing decisions on price volatility in developing countries. To address this, we modify the Deaton and Laroque model in two ways: we introduce liquidity constraints and heterogeneous information about grain availability. These two factors play an important role in farmers' marketing decisions in Burkina Faso, and may explain why rural prices in developing countries do not exhibit the same patterns as international commodity prices.

Empirical observations that support the competitive storage model by Deaton and Laroque (1992) are characterized by two features: price series distributions always exhibit a positive skewness (upward price spikes are more frequent or have a greater magnitude than downward spikes) and almost always exhibit a positive kurtosis (the price distribution has greater peakedness than the normal distribution, for the same variance). These properties are attributed to the effect of storage in smoothing price shocks in general, and downward price shocks in particular. Deaton and Laroque build a storage model that generates simulated price series that are characterized by these two properties.

After analyzing 33 monthly maize price series arising from 33 marketplaces in Burkina Faso, however, we obtained 33 price distributions that do not exhibit these properties. Instead, kurtosis is frequently negative, which indicates that price fluctuations are greater in our distributions than in a normal distribution, and skewness is frequently negative in the post-harvest season, indicating either more frequent or more severe price drops than in a normal price distribution (see Table 1).

In this article, we investigate whether these atypical price patterns may be related to liquidity constraints and heterogeneity in price expectations. To do so, we adapt the competitive storage model in order to analyze the role of farm storage on price volatility.

In Section 2, we provide a background on the drivers of farm storage that have been studied in the literature to date. In Section 3, we introduce a liquidity constraint and expectation errors in the competitive storage model and analyze how these factors

*Corresponding author. Tel.: + 33 6 80 45 75 00; fax: +33 4 67 61 55 37. *E-mail address*: elodie.maitredhotel@cirad.fr (E. Maître d'Hôtel).

DOI: 10.1111/agec.12396

Table 1
Average characteristics of price distributions in 33 market (SONAGESS data)

	Observation per market	Average price	Average std	Average skewness	Average kurtosis	Markets with negative skewness	Markets with negative kurtosis
complete series	121	134.87	31.39	0.25	−0.21	3	15
pre-harvest season	52	140.52	36.36	0.33	−0.40	4	27
Post-harvest season	69	130.58	26.32	0.11	0.17	15	14

modify storage decisions and price behavior over the course of a year. In Section 4, we describe our empirical strategy. Employing ARCH models and dynamic panel analysis over the 2005–2012 period, we combine original household and price data to test the role of farm storage on price volatility in local markets. In Section 5, we demonstrate that carryovers are associated with unexpected price drops in the preceding year and that carryover is associated with an increased frequency of unexpected price drops at the beginning of a new year.

2. Background on farm storage

Several analyses of the role of stockholder decisions on price dynamics have demonstrated that, in standard cases, storage management has a smoothing effect on price volatility (Wright, 2011). A key feature of this literature rests on the "buy low, sell high" principle (Gustafson, 1958), by which the optimal storage and sale of grain stocks tends to mitigate price shocks. This is at the root of the competitive storage model, originally applied to commodities that can be stored for more than a year and are subject to random production shocks (Cafiero et al., 2011; Deaton and Laroque, 1992; Gustafson, 1958). Analyses of price series data (Bobenrieth et al., 2013; Deaton and Laroque, 1992; Serra and Gil, 2013), as well as simulations have given empirical support to this model (Deaton and Laroque, 1992; Frechette, 1999).

However, the scarcity of storage data series has limited the number of direct empirical tests of the relationship between storage and prices. Some have used monthly storage forecasts (Shively, 1996) or historical monthly prices as a proxy for storage data (Serra and Gil, 2013). At the macroeconomic level, there are results on the relationship between the stock level and price volatility.[1] At the domestic or infradomestic level, the role of public storage on price volatility is also well documented (Barrett, 1997).We contend, however, that the relationship between farm storage and price volatility has not been modeled or empirically assessed. We ask, can the competitive storage model account for the price pattern observed in rural Burkina Faso, and if so, under what modifications?

A primary difference between commercial stockholders and farmers arises from the farmer's market participation issue. As a result of high transaction costs, farmers' sales prices may be inferior to their purchase prices (Bellemare and Barrett, 2006; De Janvry et al., 1991; Key et al., 2000), which hinders their market participation. Because of this, their reactions to price shifts are not as systematic as depicted in the competitive model. A price increase produces a sale only if the sales price rises above the farmer's shadow price, which is equal to the farmer's marginal utility for the grain. Prioritizing food security can also limit their willingness to sell even when prices are high (Fafchamps, 1992; Kazianga and Udry, 2006; Saha and Stroud, 1994). During the lean season, grain prices are generally high, and farmers have an incentive to sell grain; despite this, they may instead prefer to keep their grain in order to ensure family consumption until the next harvest, as possessing an adequate stock of grain prevents them from buying food when prices are high (Park, 2009). This seasonal pattern has been described in many African contexts (Bellemare and Barrett 2006; Kazianga and Udry, 2006; Saha and Stroud, 1994). However, the bounded market participation limits both sales and purchases, thus should not eliminate positive skewness of price distribution due the stock nonnegativity constraint.

A second difference between commercial stockholder and small-scale farmers is the importance of liquidity constraints due to poor access to credit and low cash savings. Both the "buy low" and the "sell high" guiding principles at the core of the competitive storage model are unattainable for farmers whose liquidity comes from grain sales (Fackler and Livingston, 2002). Prices in Africa follow a cyclical pattern every year: grain prices are at their lowest level during the harvest season and then increase until the lean season when they reach their peak. The predictability of this price dynamic creates incentives to purchase grain during the harvest season and store it until the lean season in order to sell it at a high price. This strategy would attenuate price seasonality, but it does not, in fact, characterize the behavior of most farmers. Under strong liquidity constraints during the harvest season, farmers can satisfy their cash needs only by selling grain at low prices, contributing to further price decreases. This occurs at a time when, according to the competitive storage model, they "should" be buying grain instead. In this case, the storage-price relation is the opposite of that which is presented in the standard model and ultimately, farm storage may be better described by a "sell low, buy high" principle (Stephens and Barrett, 2011). This constraint to purchase could explain small or negative skewness of price distributions.

A third difference is that farmer price expectations may not obey standard assumptions. Farmers are heterogeneously

[1] It has been observed that periods with low stocks correspond to price spikes on world markets (Wright, 2011). When stocks are low, a small production or consumption shock can have large impacts on price because adjustments are characterized by greater inelasticity (Gilbert and Morgan, 2010).

informed, and it is likely that they also vary in their capacity to formulate price expectations based on the information available to them (Chavas, 2000). The standard notion of rational expectations rests on two assumptions: (i) perfect information about the present (uncertainty only exists in regard to future shocks) and (ii) uniform expectations (Deaton and Laroque, 1992; Muth, 1961). In this framework, agents use available information to derive optimal storage decisions and the only source of price volatility is random shocks to future harvests. These assumptions have been relaxed by several authors. In attempts to add "realism" to the analysis (Peterson and Tomek, 2005), the hypothesis of perfect information has been relaxed, generating the concept of bounded rational expectations and led to models of adaptive expectations.[2] These models lead to an endogenous source of price fluctuations, caused by expectation errors. Under this assumption, storage decisions may be nonoptimal and reinforce, rather than mitigate, price fluctuations. Several models of endogenous price fluctuations that integrate storage strategies have been developed recently (Berg, 2016; Femenia, 2015; Mitra and Boussard, 2012).[3] These models show that seasonal storage decisions increase the likelihood of chaotic price fluctuations (Mitra and Boussard, 2012), that storage subsidies may, on average, destabilize agricultural markets (Femenia, 2015), and that higher expected prices and resulting reductions in farm storage may increase volatility (Berg, 2016). Our article is related to these three papers in that we analyze the impact of expectation errors on storage strategies and resulting price volatility. Nevertheless, our assumptions and methods are different: errors in our model arise from imperfect information on grain availability in the village, and we use real price and storage data[4] in order to provide an empirical measure of expectation errors and their effect on storage and prices. In the three mentioned models, with the exception of Mitra and Boussard (2012) who extend the model to include two seasons, each suboptimal production decision generates a price deviation from its equilibrium, implying that production decisions occur as frequently as observed price shifts. This cannot be the case in intra-annual models. In this article, we assume that expectation errors are not caused by errors in production forecast, but by imperfect information on stock availability. We thus relax the assumption of rational expectations, according to which decision makers know the current volume of aggregated stock.

3. The seasonal dynamics of storage

We introduce two aspects of farm storage into the standard competitive storage model: liquidity constraints and heterogeneous expectations.[5]

3.1. A liquidity constraint in the competitive storage model

In the Deaton and Laroque (1992) model, the profit from holding inventory I_t from period t to $t+1$ is given by

$$[\,(1-\delta)\,E_t\,p_{t+1}]\;\;I_t;\quad I_t \geq 0, \tag{1}$$

where β is the discounting factor, δ is the stock spoilage rate, p_t is the grain price at period t, and E_t is the expectation conditional on information available at t, which is the amount of grain on hand at t. This amount is equal to harvest z_t if there is harvest at t plus the depreciated amount of grain that was stored during the previous period $(1-\delta)I_{t-1}$. Since t is a monthly index in our framework, z_t is equal to zero every month except for the month of harvest.

This model assumes that the stockholder can purchase grain without restriction.[6] In the case of a liquidity constraint, an agent expecting a price increase may not be able to purchase grain if this agent has nothing to offer but grain. Imposing a liquidity constraint in order to account for the situation of most farmers in Burkina Faso, the model is modified by the addition of the following restriction:

$$I_t \leq (1-\delta)\,I_{t-1} + z_t. \tag{2}$$

Present stock is composed of previous period stock plus present harvest, if there is any. Farm stock can no longer increase between two periods without harvest.[7]

[2] The perfect information assumption regarding grain availability is less plausible in African villages because information on grain stocks is of strategic importance for food security. The reputational threat associated with having grain but refusing to help a hungry person is so strong that farmers have no choice but to help, that is, unless people believe they have virtually no grain at home. As a result of this social pressure, farmers tend to conceal their stock of grain, especially during the lean season. It is thus unlikely that farmers would be aware of the true level of stock in the village.

[3] Models with heterogeneous expectations, primarily used in finance, have also been developed in order to better fit actual price series data (Branch, 2004) and to assess the expectation learning process through experiments (Hommes, 2011). Theoretical work has shown that models that incorporate expectation error have the potential to account for greater volatility than perfect information models (Grandmont, 1998).

[4] Most of the research on endogenous factors contributing to price dynamics consists in developing theoretical models that are used to simulate price series that are as consistent as possible with the distribution of observed prices (Berg, 2016; Mitra and Boussard, 2012) as well as to simulate changes in the system (Femenia, 2015).

[5] Other dimensions of farm stock management, such as consumption risks (Kazianga and Udry, 2006) or transaction costs (De Janvry et al., 1991), may play a role in price volatility, but are not under the scope of this article.

[6] Net buyers of grain are not included in the supply side of our model, but in the demand side. Since net buyers have some nongrain source of cash, they are not subject to the binding liquidity constraint described in our model. As in the competitive storage model (Eq. (9)), the demand for grain depends on present prices only, and thus does not impact volatility. This is a simplification of reality, as the demand of net buyers may also depend on their farm stock, price expectations, as well as irregular sources of income (e.g., animal sales, nonfarm activities, and family transfers), all of which may affect price volatility. Incorporating these elements would significantly increase the complexity of the model.

[7] Note that farmers are seen here as profit-maximizing agents. It implies, in particular, that consumption is not explicit, as it is in typical household models. Grain storage destined for own consumption is considered to be exogenous and

Restriction (2) reflects the absence of credit and savings, as well as alternative sources of cash. If alternative sources of income exist, the liquidity constraint either disappears or decreases. After maximizing profit, in the general case where the farmer has not already stocked out at $t-1$,[8] storage decisions are given by the following:

$$I_t = 0 \quad \textit{if } (1-\delta)E_t p_{t+1} < p_t, \tag{3}$$

$$0 < I_t < (1-\delta)\, I_{t-1} + z_t \quad \textit{if } (1-\delta)E_t p_{t+1} = p_t, \tag{4}$$

$$0 < I_t = (1-\delta)\, I_{t-1} + z_t \quad \textit{if } (1-\delta)E_t p_{t+1} > p_t. \tag{5}$$

As in the standard model, if there is an expected loss of holding storage, as in Eq. (3), the agent sells grain, which drives the price down (p_t decreases). If there is still an expected loss from storing grain when only one unit of grain remains in the warehouse, the agent sells out his stock and storage is zero, $I_t = 0$.

However, if the price decrease due to the sale is such that the agent has not stocked out all of his grain when the expected profit of holding grain equals the present profit of selling grain, the agent maintains a strictly positive level of storage (Eq. (4)). This is also described in the standard model.

The difference between our model and the standard model arises from Eq. (5). When expected prices are high enough, there is a strictly positive profit from holding stock, and the agent holds his entire stock until the next period. If the agent could purchase grain, price p_t would increase until $(1-\delta)E_t p_{t+1} = p_t$. At this equilibrium, the agent would stop purchasing grain and inequality in Eq. (5) would never be observed, as in Deaton and Laroque's model. Since the farmer cannot purchase grain, he simply retains the entire stock until $t+1$ and price does not increase in t, so that inequality (5) holds. This is consistent with negative or no skewness in price distribution: storage fails to regulate downward price spikes (Eq. (5)) and stock nonnegativity fails to regulate upward spikes (Eq. (3)).

Because of Eq. (5), the theorems on stationary rational expectations equilibrium proposed by Deaton and Laroque (1992) do not hold in the presence of a liquidity constraint. In this case, the market price is no longer a maximum of two possible definitions (3) and (4). Instead, the actual price may now be inferior to the discounted expected price, and moreover, may not converge toward this expected discounted price.

This explains why, contrary to what is observed in international commodity markets by Deaton and Laroque (1992) or Wright (2011), price drops can be at least as strong as price peaks in domestic markets in which farmers and stockholders face liquidity constraints. The conditions required in order to observe the stabilizing effects of storage on volatility as described in the competitive storage model are met less frequently in countries with limited credit availability like Burkina Faso.

3.2. Heterogeneous price expectations

We introduce heterogeneous expectations and analyze how they produce suboptimal storage decisions. Farmers in a village may infer the total amount of stock in the village from their own stock level, and the quality of this inference is likely to vary across farmers. For instance, large-scale farmers are presumably better at inferring the total stock level from their own stock than small-scale farmers. Given this heterogeneity in information, it is reasonable to expect that not all farmers can anticipate prices with the same degree of accuracy, and that this impact price expectations and thus storage decisions.[9]

Over a population of N farmers in the village, assume that n farmers' expectations are such that $\beta(1-\delta)E_t^n p_{t+1} \leq p_t$, and $N-n$ farmers' expectations are such that $\beta(1-\delta)E_t^{N-n} p_{t+1} > p_t$. This can occur, for instance, if n farmers hold a large stock and believe that the $N-n$ farmers hold a greater stock than they actually have, or if the $N-n$ farmers hold little stock and believe that the n farmers have less stock than they actually have. Equation (3) shows that the n farmers sell out their stock if $\beta(1-\delta)E_t^n p_{t+1} < p_t$ after they have sold out and Eq. (4) shows that they sell some grain if $\beta(1-\delta)E_t^n p_{t+1} = p_t$ before they have sold out. However, since the $N-n$ hold little stock in reality, the price is likely to increase between t and $t+1$, more than the n farmers had anticipated. At t, the n farmers underestimate p_{t+1}.

Symmetrically, Eq. (5) shows that the $N-n$ farmers hold their stock from t to $t+1$. If the n hold more stock than the $N-n$ believe they do, the price at $t+1$ is likely to increase less than expected by the $N-n$, and may even decrease. This describes be a price overestimation by the $N-n$.

This section aims to understand how expectation errors influence storage. A price expectation error is defined as the difference between the expected price for $t+1$ and the actual price realized at $t+1$, $\eta_{t,t+1} = E_t p_{t+1} - p_{t+1}$. A price overestimation occurs when $\eta_{t,t+1} > 0$ and a price underestimation occurs when $\eta_{t,t+1} < 0$.

separate from the grain stock that is stored to maximize profits. In support of this assumption, farmers in Burkina Faso typically consume their grain (maize, millet, or sorghum) twice a day (the "Tô"), and purchase meat, fish, vegetables, oil, or spices as their income and market prices allow. As long as they are net sellers, the amount of grain eaten by farmers is nearly inelastic.

[8] i.e., $I_{t-1} > 0$ or $z_t > 0$. If $I_{t-1} = z_t = 0$, then $I_t = 0$.

[9] Although standard models assume that price expectations are formulated based on information about the amount of grain on hand in the household, information about the total amount of grain on hand in the village would arguably be more relevant for formulating correct price expectations. If farmers conceal the true level of stock that they have, each farmer is left with only a belief about the aggregate amount of stock in the village. Furthermore, farmers who have had an abundant harvest would be more likely to believe that other farmers have also had a good harvest and therefore would also be more likely to overestimate total stock in the village. Similarly, these farmers would be less likely to anticipate a resource shortage at the village level for the next period and accordingly, less likely to anticipate a high price of grain in the next period compared to farmers who possess a low stock of grain.

First-order conditions can be written in terms of expectation errors:

$$\text{if } \eta_{t,t+1} < \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad I_t = 0, \tag{6}$$

$$\text{if } \eta_{t,t+1} = \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad 0 < I_t < (1-\delta)I_{t-1} + z_t, \tag{7}$$

$$\text{if } \eta_{t,t+1} > \frac{p_t}{\beta(1-\delta)} - p_{t+1}, \quad I_t = (1-\delta)I_{t-1} + z_t > 0. \tag{8}$$

The interpretation of these conditions rests on the sign of $\eta_{t,t+1}$.

3.2.1. Price overestimation situations, $\eta_{t,t+1} > 0$

The effect of a price overestimation differs depending on whether the price decreases or increases less than expected.

If the price drops or moderately increases between t and $t+1$, such that $\frac{p_t}{\beta(1-\delta)} > p_{t+1}$, the optimal choice at t would be to stock out. The actual storage decision at t depends on the size of the error. If the error is small enough as in (6), the farmer stocks out. The expectation error does not produce a storage error. If the error is large enough as in (8), the farmer holds the entire stock, and storage error is maximal.

If the price increase is intermediate, such that $\frac{p_t}{\beta(1-\delta)} = p_{t+1}$, the overestimation leads farmers to hold their stock, whereas the optimal decision would have been a partial stock release.

If the price increases sharply between t and $t+1$ (less than expected), such that $\frac{p_t}{\beta(1-\delta)} < p_{t+1}$, the optimal decision is to hold their stock, which is also the actual decision. The price overestimation has no consequence in this case.

To summarize, if I^*_{t+1} denotes the optimal inventory in $t+1$, that the farmer would have held if he made no error in t, the extrainventory, i.e., $I_{t+1} - I^*_{t+1}$, is positive or nil in case of a proce overestimation in t. A more rigourous and detailed development of different subcases is presented in the online appendix, leading to Proposition 1.

Proposition 1. *Sufficient conditions for expectation error at t to generate extra inventory at*

$$t+1 \text{ are } \begin{cases} 0 \le \frac{p_t}{\beta(1-\delta)} - p_{t+1} < \eta_{t,t+1} \\ p_{t+1} < \beta(1-\delta)E_{t+1}p_{t+2} \end{cases}.$$

The first condition implies that the actual price change is a price decrease or a small increase (compatible with stocking out), whereas the farmer believes in a stronger price increase (incompatible with stocking out); the second condition implies that the farmer's expectations at $t+1$ do not produce stocking out in $t+1$ (which would suppress the effect of the error).

3.2.2. Price underestimation situations

In the case of a sufficient price increase between t and $t+1$, $\beta(1-\delta)p_{t+1} > p_t$, the optimal behavior would be to hold the entire stock from t to $t+1$ (Eq. (5)), i.e., $I^*_{t+1} = (1-\delta)I_t + z_{t+1}$. We show that underestimating the future price favors lower-than-optimum stocks or stock-out (proof in the online appendix).

In the case of a price decrease or moderate price increase (compatible with optimal stocking out), the error makes no difference since it does not prevent stocking out.

Proposition 2. *Sufficient conditions for expectation error at t to generate underinventory at*

$$t+1 \text{ are } \begin{cases} \eta_{t,t+1} < \frac{p_t}{\beta(1-\delta)} - p_{t+1} \le 0 \\ p_{t+1} < \beta(1-\delta)E_{t+1}p_{t+2} \end{cases}.$$

3.3. Price expectation errors and carryover

Carryover is defined as the stock that remains on hand at the end of a crop season and before the new harvest is realized, e.g., in October. There are few models based on monthly decisions that are derived from the competitive storage models and that permit carryover of an annual harvest into the following year (Peterson and Tomek, 2005). Frechette (1999) develops a storage model, assuming that the decision to retain carryover can be a rational decision akin to investing in self-insurance in the case of a bad harvest. We suggest here the alternative explanation that carryover may result from expectation errors.

3.3.1. The link between unexpected price drops in the lean season and subsequent carryover

In general, price declines occur at the time of the harvest or slightly before the harvest, and farmers expect this price drop to happen even if they do not know precisely when it will occur. If farmers could accurately anticipate this drop, our framework suggests that they would sell out their stock before it happens, and carryover would not exist. However, due to events such as changes in regional supply generated by harvests in neighboring countries, prices can drop before they are expected to. Farmers who do not anticipate this price drop miss the last occasion to sell before the new harvest arrives and further depresses the price of grain.

If the harvest in the village begins at $t+1$, the stock on hand at $t+1$ represents carryover from the previous harvest. Applying Proposition 1 to this period, we get Result 1.

Result 1. *Unexpected price drops occurring before harvest tend to increase carryover.*

3.3.2. The link between carryover and post-harvest unexpected price drops

Analyzing the link between carryover and prices requires market clearing conditions. As in the standard model, we assume that at $t+1$,

$$p_{t+1} = P\left((1-\delta)I^N_t + z^N_{t+1} - I^N_{t+1}\right), \tag{9}$$

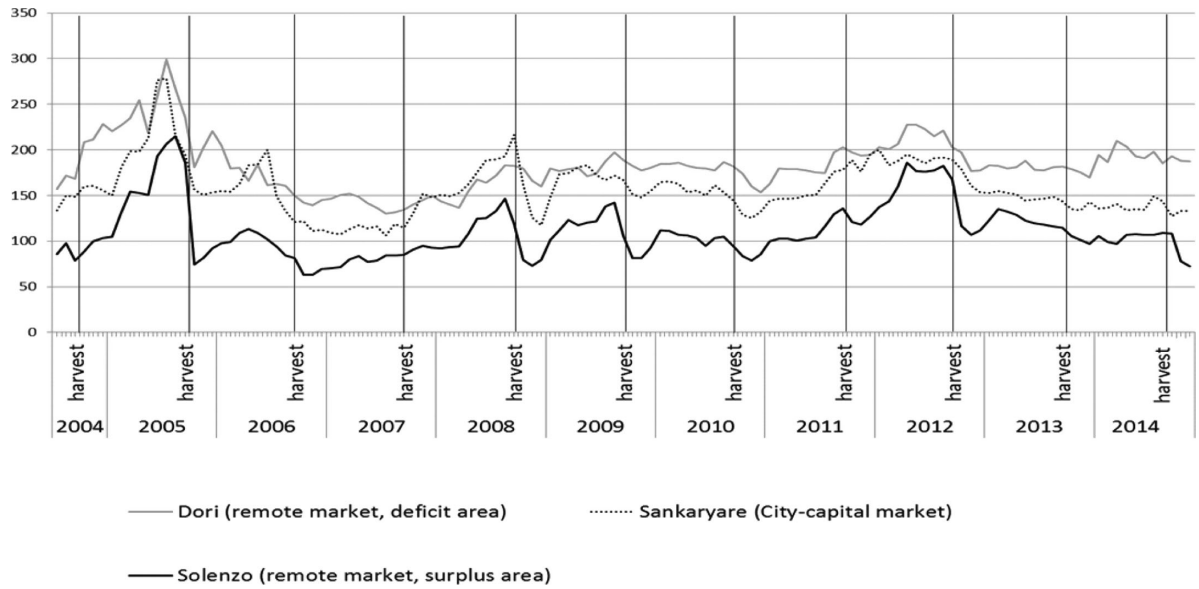


Fig. 1. Real maize prices in Burkina Faso, 3 markets, 10 years (SONAGESS data).

where $P(.)$ is the inverse demand function. Farmers' expectations of the price in $t+1$ can be written as the expected inverse demand function depending on their own inventory and their belief about the inventory of other farmers.

$$E_t^n p_{t+1} = E_t^n P\left((1-\delta)\left(I_t^n + \hat{I}_t^{N-n}\right) + z_{t+1}^N - I_{t+1}^N\right), \qquad (10)$$

where $\hat{I}_t^{N-n}$ is the n farmers' belief about the amount of stock held by the $N-n$.

We are interested in the case in which the n farmers have stocked out and believe that the $N-n$ farmers have also stocked out. In this case, $E_t^n p_{t+1} = P(z_{t+1}^N - I_{t+1}^N)$ and $\eta_t^{t+1} = P(z_{t+1}^N - I_{t+1}^N) - P((1-\delta)I_t^{N-n} + z_{t+1}^N - I_{t+1}^N) > 0$. This implies that the existence of carryover held by the $N-n$ produces a price overestimation by the n, if the latter ignore this carryover. In addition, if $p_{t+1} < p_t$, this price overestimation is an unexpected price drop (for the n farmers).

Result 2. *Greater carryover favors unexpected price drops after the harvest.*

The empirical relevance of the two above results is tested in Section 4 of this article.

4. Empirical strategy

4.1. Data on maize price

SONAGESS (Societe Nationale de Gestion du Stock de Securite) collects maize prices on a weekly basis in 48 markets throughout the country, and publishes monthly prices. We use a subset of 33 series of maize prices with no discountinuities over the 2004–2014 period. Monthly prices have been deflated using the Burkinabe Consumer Price Index obtained from the INSD (Institut National des Statistiques Demographiques). The evolution of maize producer's real prices is represented in Fig. 1 for three markets: one market in a surplus area, one in a deficit area, and a third in the capital city of Ouagadougou. Grain prices are higher in deficit areas than in surplus areas and follow a seasonal dynamic, with maximum prices occurring between July and September, corresponding to the lean season in Burkina Faso, and minimum prices occurring between October and December, corresponding to the harvest season. In each of the three markets studied, price peaks were quite pronounced in 2005, 2008, 2012, and to a lesser extent in 2009. In these years, price peaks were mainly associated with poor harvests, which were related to events such as insect infestations (2005), episodes of drought (2009 and 2012), and international price spikes (2008 and 2012). Price rises are less accentuated following good harvest years (as in 2013), and even less so in surplus areas. This indicates that in these surplus areas, farmers are more likely to have stocks left over to sell during the lean season, which limits price spikes. Furthermore, although the magnitude of price spikes is somewhat greater than the magnitude of price drops, price drops are clearly present, contrarily to what is frequently observed (Deaton and Laroque, 1992).[10]

4.2. Data on maize production and storage

The Burkinabe Ministry of Agriculture has been collecting data on agricultural production through the implementation of a panel rural household survey since 1992. Once a year, an average of 4,500 rural households are interviewed and their agricultural production is measured. The panel survey is conducted using a two-stage stratified randomized design. First,

[10] See notably the figure on annual international sugar price between 1930 and 1990.

villages are randomly chosen in each province, where the relative number of villages per province is dependent on the relative population of each the 48 provinces in Burkina Faso. In the second stage, five households are randomly selected in each of the selected villages. This two-stage process ensures that the surveyed households are representative of rural households both at the province and national levels, which justifies our use of aggregate province-level data to analyze storage behaviors. The storage data we use come from a subset of 3,160 households, located across 33 different provinces with complete price series. From this subset, we also make use of data on annual maize production as well as maize carryover, which is defined as the amount of on-farm maize stock remaining when the next harvest season arrives following the end of the lean season. Individual data have been aggregated at the province level corresponding to the 33 markets analyzed. Carryover is measured once a year for 33 different provinces over 8 years. Prices are measured once a month for the 33 different provinces over 10 years.

The final panel database is composed of 33 markets for which we have yearly carryover data over 8 years (2005–2012) and price data over 10 years (2004–2013). Descriptive statistics on maize price, storage, and production in each of the 33 markets are given in Table 8 in the online appendix.

4.3. Measuring volatility

In recent literature, price volatility is defined in this article as the unpredictable component of price variations. Predictable price variations, like price seasonality or price trend, are not part of price volatility. The empirical measurement of volatility requires assumptions regarding the information available to agents and their ability to anticipate prices. A commonly used model to distinguish the predictable and the unpredictable part of price variation is the autoregressive conditional heteroskedastic (ARCH) model (Apergis and Rezitis, 2003; Barrett, 1997; Gilbert and Morgan, 2010; Maître d'Hôtel et al., 2013; Serra and Gil, 2013; Shively, 1996). A mean equation provides the predictable price at t conditional on information available at $t-1$ and a conditional variance of the error term of the mean equation provides a measure of price volatility that changes with t.

Because we have one price series for each market, we estimate a common specification of such model for each price series, based on a unique ARCH structure. The ARCH model structure is as follows:

$$P_{mt} = \beta_0 + \beta_1 P_{mt-1} + \sum_{i=1}^{11} \beta_i D_i + \varepsilon_{mt} \quad \varepsilon_{mt} : N(0, h_{mt}), \quad (11)$$

$$h_{mt} = \alpha_0 + \alpha_1 \varepsilon_{mt-1}^2 + \nu_{mt} \quad \nu_{mt} : N(0, \sigma), \quad (12)$$

where the subscript m denotes the market index.

Equation (11) is the mean equation that determines the deflated producer price of maize as a one-order autoregressive process. D_i is a monthly dummy variable taking the value 1 for month i. A one-order autoregression was selected after testing the number of significant periods in each individual market. While introducing P_{t-2} and P_{t-3} in the model is significant for some markets, we elect to use a unique and parsimonious model structure for each market in order to facilitate the comparability of predicted prices across markets. A trend variable was tested and rejected due to low statistical significance. Equation (12) determines the conditional variance of the error term ε_{mt} as a function of the shock in the previous period and confirms the significant ARCH nature of the price process in 20 out of the 33 villages. In the 13 remaining villages, the price process is autoregressive with homoscedastic variance.[11]

4.4. Measuring unexpected price drops and spikes

We conduct the estimations above for each of the 33 markets so as to obtain 33 series of price volatility. Next, we segregate each series into two: the series of conditional variances for negative unexpected price shocks and the series of conditional variances for positive unexpected price shocks. We then calculate the average variance for each series over a period of time varying from 1 month to 12 months in order to examine the robustness of the relationship between volatility and carryover. The occurrence of positive price spikes in market m, for year j between month τ_0 and month τ_1 is calculated as follows:

$$h^+_{mj\tau_0\tau_1} = \frac{1}{\tau_1 - \tau_0} \sum_{t=\tau_0}^{\tau_1} \hat{h}^+_{mt} = \hat{\alpha}_0 + \frac{\hat{\alpha}_1}{\tau_1 - \tau_0} \sum_{\substack{t=\tau_0 \\ \varepsilon_{mt>0}}}^{\tau_1} \varepsilon^2_{mt-1}. \quad (13)$$

A similar calculation is made for $h^-_{mj\tau_0\tau_1}$, the occurrence of unexpected price drops in market m for year j between month τ_0 and month τ_1.

4.5. Estimating the link between unexpected price drops during the lean season and carryover at the end of the lean season

Carryover is empirically specified by

$$\chi_{mj} = \gamma_0 + \gamma_1 \chi_{mj-1} + \gamma_2 h^-_{mj\tau_0\tau_1} + \gamma_3 y_{mj-1} + \varepsilon_{mj}$$
$$\varepsilon_{mj} : \quad N(0, \sigma_\varepsilon) \;\; m = 1, \ldots, 33 \;\; j = 2005, \ldots, 2012, \quad (14)$$

[11] One can question whether the ARCH model accurately captures the unpredictable component of price changes for farmers. If farmers are able to make better price forecasts than our ARCH model, some of what we consider to be unexpected price shifts would, in fact, be expected. This would lead to an overestimation of expectation errors. Although possible, we do not find this case very likely because the ARCH model is known to make accurate forecasts. A more likely mismatch occurs if the model makes better forecasts than farmers, leading us to underestimate expectation errors. In the online appendix, we provide a robustness check using a coefficient of variation as a measure of price variation that includes seasonal variations and trend, and which produces consistent results. This confirms that most price shifts are unpredictable for some farmers. The ARCH model residuals should be interpreted as a measure of what is unpredictable for all farmers and the coefficient of variation includes fluctuations that are unpredictable for the less informed farmers only.

where χ_{mj} is the average amount of carryover in region m at the end of the lean season of calendar year j and y_{mj-1} is the grain harvest at the end of calendar year $j-1$.

According to Result 1, we expect carryover to increase with unexpected price drops during the lean season, when prices are expected to reach their annual peak, that is, $\gamma_2 > 0$ for τ_0 varying from November of year $j-1$ to October of year j and τ_1 varying from September to October of year j. The variable summarizing unexpected price drops $h^-_{mj\tau_0\tau_1}$ is measured during the period preceding the carryover. Since no theoretical prediction exists regarding the length of the period, we test different lengths from 1 month to 1 year. The fact that this explanatory variable corresponds to the period preceding the measurement of carryover does not guarantee a causal link between the two when these measures are correlated (Bellemare et al., 2015). In a village of more educated farmers, for example, strategic stock management leading to optimal carryover decisions as well as the absence of expectation errors could both result from high education levels. In this case, education could simultaneously be the cause of no carryover and no expectation error. It is often argued that the fixed effects in a panel estimation can theoretically control for this type of simultaneous unobserved causality (e.g., the quality of information), but it is also arguable that this only reduces endogeneity. Education, for instance, is not necessarily fixed.

Our approach consists in using several measures of expectation error to test the strength of the correlation between unexpected price drops that occur between the harvest and lean season, and the carry over at the end of the lean season.

4.6. Estimating the relationship between post-lean season carryover and post-harvest unexpected price drops

The empirical specification for the variance of unexpected negative price shocks is given by

$$h^-_{mj\tau_0\tau_1} = \rho_0 + \rho_1 h^-_{mj-1\tau_0\tau_1} + \rho_2\chi_{mj} + \rho_3 y_{mj-1} + \eta_{mj}$$
$$\eta_{mj}: \quad N(0,\sigma_\eta) \quad m = 1,\ldots,33 \quad j = 2005,\ldots,2012 \tag{15}$$

Result 2 predicts that the occurrence of unexpected price drops around the harvest season increases with the amount of carryover that remains after the end of the previous lean season, that is, $\rho_2 > 0$ for τ_0 varying between September and November and τ_1 varying between October and March.

Both panel equations[12] are estimated using the generalized moments method following the Arellano and Bover/Blundell and Bond procedure with predetermined variables (Arellano and Bover, 1995; Blundell and Bond, 1998).[13] The dynamic panel procedure generates moment conditions using lagged values of the dependent variable and the pre-determined variables with first differences of the disturbances. Because the autoregressive process is persistent, we must obtain additional moment conditions in which the lagged differences of the dependent variable are used as instruments (Arellano and Bover, 1995; Blundell and Bond, 1998). Lagged production and lagged prices are used as pre-determined variables, and the dummy variables of fixed market effects are used as exogenous variables. Table 9 in the online appendix describes the volatility variables for the 33 markets we analyze.

5. Results

5.1. Price general characteristics

As observed elsewhere, our price series exhibit a positive skewness, but the average coefficient is much lower in our case (0.25) than in Deaton and Laroque (1.18 for maize), implying that local monthly prices in rural areas may also be asymmetric, though to a lower extent. Furthermore, for post-harvest periods (November–May), skewness is negative in 15 of the 33 villages, indicating huge price drops that challenge the classical asymmetric stylized fact.

Kurtosis is negative in more than half of marketplaces, which indicates a flatter distribution than in the normal distribution (i.e., greater price fluctuations). Average kurtosis is −0.21 in our price series (versus +2.48 in Deaton and Laroque).

5.2. Price volatility

The mean equation in the ARCH model shows that prices follow an autoregressive process with large and significant monthly autocorrelation, and that pre-harvest prices are significantly higher than prices during the rest of the year, while post-harvest prices are significantly lower. These results are consistent with those of Shively (1996), Barrett (1997), and Karanja et al. (2003). For a deflated price index with a mean of approximately 100 (depending on the markets), the seasonal average difference between high and low prices is around 10.

Fig. 2 depicts the annual evolution of average prices and average unexpected price drops and spikes. Month 1 denotes January, etc. This evolution illustrates that, even after price series are deseasonalized, the frequency of large positive price shocks is not the same throughout the year. Prices are, on average, higher between June and August and unexpected price shocks occur most frequently in July. Conversely, negative price shocks occur mainly in October, when prices are lower. Note that the harvest period (October–November) is both a period of price drops and price spikes, meaning that there are, on average,

[12] Our panel may exhibit substantial cross-sectional dependence which could arise due to the presence of common price shocks and spatial dependence between different markets. We tested for the existence of such dependent price dynamics between markets in our panel data models: the Friedman test rejects the existence of cross-sectional dependence between the price dynamics in our different markets, both for negative and positive volatility models.

[13] Price series stationarity is verified with an augmented Dickey Fuller test.

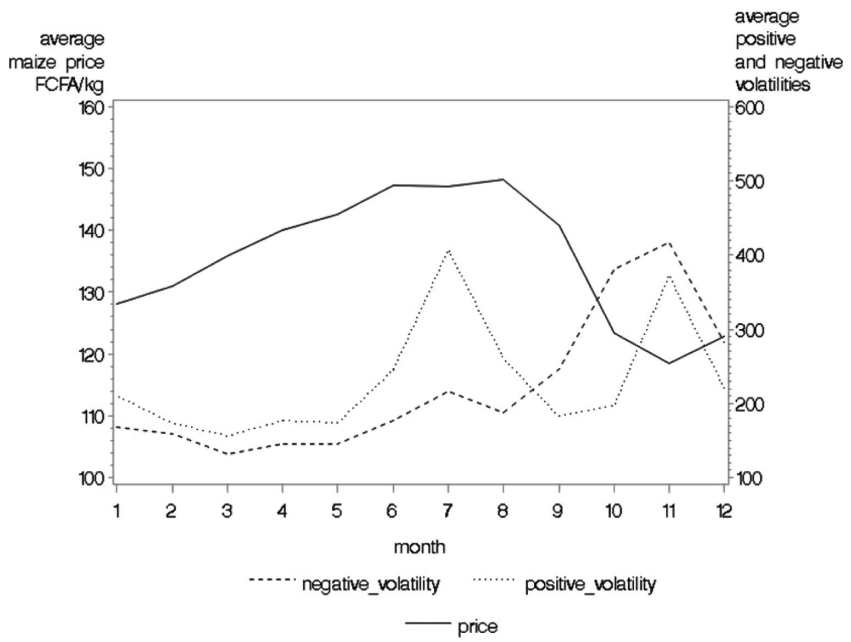


Fig. 2. Average unexpected price drops and spikes over the year in Burkina Faso, 33 markets, 10 years (from SONAGESS data).

more unexpected drops and peaks during these months. Unexpected peaks could occur due to low harvests, generating price increases earlier than usual, whereas unexpected price drops could occur due to unobserved carryovers. Figure 2 also illustrates that carryovers measured before the harvest in September may impact the frequency of unexpected price drops as long as these carryovers increase sales.

Descriptive statistics on average volatilities for the 33 markets we study are given in the online appendix.

The frequency of unexpected price drops and spikes within a year is depicted in Fig. 3.

5.3. The link between volatility and subsequent carryover

The model predicts that carryover at the end of the farming year should be zero if no unpredicted price drop has preceded the harvest. If many significant unexpected price drops have occurred before harvest, it is likely that several farmers have missed the opportunity to sell their stock on time, and thus, the amount of carryover should be large (Result 1). This is confirmed by the estimation presented in Table 2, which indicates that not all farmers who still have stock during the lean season anticipate price drops correctly, causing some to miss their chance to sell out before the price drop occurs. The eight different specifications correspond to different time frames over which price volatility is measured. Specification [1] covers one yearly cycle, from the post-harvest season in November to October of the following year. Specifications [2]–[8] consider the lean season specifically. Unexpected price drops occurring during the lean season (July–September, specification [4] in Table 2) tend to increase the amount of carryover at the 5% level, as is predicted (Result 1). This feature holds for average annual price drops (specification [1]) and is even stronger for price drops observed during the lean season, i.e., the July–September period (specifications [4], [6], and [7]). Excluding September from the observed period, this result does not hold, indicating that unexpected price drops in September are critical in favoring carryover (specifications [2], [3], and [5] in Table 2).

When significant, carryover is positively correlated with previous carryover and the previous harvest.

The relationship between unexpected price spikes and subsequent carryover does not appear to be significant (see Table 5 in the online appendix).

5.4. The link between carryover and subsequent volatility

The impact of carryover on unexpected price drops is presented in Table 3, in which the different specifications correspond to different time periods over which price drops are measured.

As in our theoretical development (Result 2), carryover tends to favor episodes of unexpected price drops throughout the following year (specification [1] in Table 3), and this feature is stronger when considering shorter post-harvest periods from November to March (specifications [3]–[7]). However, this correlation tends to disappear as time progresses following the harvest (Table 3).

Another observation is that the harvest has either zero or a negative correlation with subsequent unexpected price drops. An abundant harvest certainly drives the price of grain down, but it appears that most of this effect is expected by

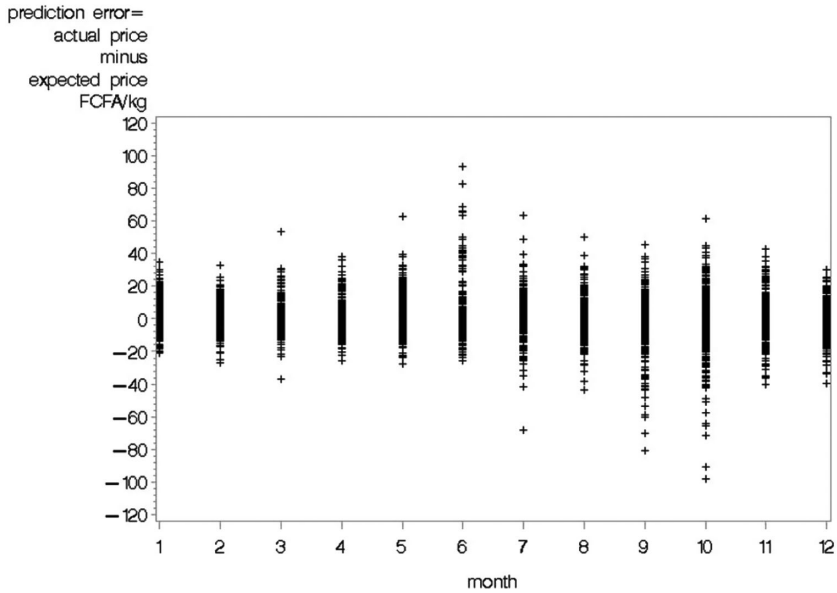


Fig. 3. Unexpected price drops and spikes within a year in Burkina Faso, 33 marketplaces, 10 years (from SONAGESS data).

Table 2
Unexpected price drops during the lean season and carryover at the end of the lean season

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Lagged carryover	0.19***	0.42***	0.15***	0.19	0.10***	0.09	0.10	0.26
Unexpected price drops	0.28**	0.38	0.57	1.13**	0.33	0.96**	1.33*	−0.02
Harvest	0.13***	0.06*	0.22*	0.06**	0.10**	0.19***	0.23***	0.06
Constant	−36.68	−60.43	−214.66	113.88*	123.39	−192.05*	−279.28	10.85
Obs.	264	264	264	264	264	264	264	264
Period used for price drops $\tau_0 - \tau_1$	November–October	July	July–August	July–September	August	August–September	September	October

Note: Significant at the * 0.1 level, ** 0.5 level, *** 0.01 level.

Table 3
Pre-harvest carryover and post-harvest unexpected price drops

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Lagged unexpected price drops	0.13	−0.12	−0.14**	−0.10**	−0.09*	0.00	0.07
Carryover	0.02**	0.09	0.12***	0.13*	0.11**	0.11**	0.06*
Harvest	−0.03*	0.01	−0.12**	−0.07**	−0.05	−0.04	−0.03
Constant	235.38**	273.63	588.70**	430.85**	368.17**	304.92**	269.24**
Obs	264	264	264	264	264	264	264
Period used for price drops	November–October	November	November–December	November–January	November–February	November–March	November–April

	[8]	[9]	[10]	[11]	[12]	[13]
Lagged unexpected price drops	−0.24	0.01	0.02	0.11	−0.14	−0.25
Carryover	0.03	0.15	0.03	−0.28	0.01	0.16
Harvest	−0.16**	−0.12	−0.01	0.02	0.01	0.00
Constant	579.20***	362.98**	240.88***	142.98***	186.92***	223.69***
Obs	264	264	264	264	264	264
Period considered for price drops	December	December–January	December–February	January	January–February	February

Note: Significant at the * 0.1 level, ** 0.5 level, *** 0.01 level.

farmers, implying that abundant harvests may not increase the occurrence of unexpected price drops. One potential interpretation of this finding is that, in a good harvest year, everyone knows the level of global production and resulting price drops are better anticipated, while in a poor harvest year, it is more difficult for everyone to judge the global harvest amount and thus massive unexpected price drops may occur.[14]

The relationship between carryover and subsequent unexpected price spikes does not appear significant (see Table 6 in the online appendix).

6. Conclusion

Most of the research on the influence of storage decisions on price volatility has focused on either public storage or speculative storage. In this article, we develop a model that analyzes the effect of farmers' storage decisions and relies on two assumptions: that farmers operate under liquidity constraints and that their price expectations are heterogeneous. We develop a theoretical model showing that the errors they make in anticipating prices increase the occurrence of extra carryover and the frequency of unexpected price drops. To check the empirical relevance of this model, we focus on maize price volatility in Burkina Faso, and we analyze the relationship between the levels of stock held by farmers and price volatility levels observed in 33 local markets over the 2004–2014 period. We differentiate between unexpected price drops and spikes and provide empirical evidence that carryovers are correlated with unanticipated price drops during the previous lean season and that this carryover increases the frequency of unexpected price drops at the beginning of the subsequent season.

This does not constitute empirical proof of a causal relationship between expectations errors and volatility, but our empirical findings are consistent with the claim that farmers do, in fact, make expectation errors and that these errors are correlated with subsequent carryover, and that this carryover is correlated with subsequent price volatility.

This suggests that some of the price volatility observed in rural markets is produced locally, as a result of the behavior of those farmers who do not have perfect information on available stocks.

Our model and empirical results support the implementation of policy measures that favor market integration and improved information dissemination. If markets were better integrated, information on existing stocks in the village would not be of such importance, implying that single transactions in villages would not have the capacity to produce price collapses that lead to extra carryovers, grain depreciation, and price volatility. We offer two suggestions regarding ways in which markets could be better integrated. First, the physical integration of villages could be improved by reducing transport costs through the building of asphalt roads and by supporting greater sharing of information between villages. When a trader enters a village and offers a low price, farmers tend to accept it, especially since they generally ignore prices in other villages given that market access to these villages is difficult. Improved market access should not decrease expectation errors regarding stocks; however, it should reduce their impact on price volatility. Second, unexpected post-harvest price drops could be mitigated through the use of policies that encourage on-farm storage just after the harvest period in order to smooth both post-harvest price drops and extreme price increases at the end of the lean season. Given the liquidity constraints that push farmers to sell much of their grain during the harvest period, this is a challenging endeavor in the context of developing countries. These constraints could be eased by subsidizing village storage infrastructures and instituting measures that facilitate greater farmer access to credit. Systems of inventory credit that are currently being developed in Burkina Faso, Ghana, Mali, and Niger allow farmers access to credit after the harvest without having to sell their stock at a low price. These systems favor longer storage periods and a reduction in sharp post-harvest price drops, and constitute an interesting issue for future applied research on volatility.

[14] A robustness test is presented in Table 7 in the online appendix, where volatility is measured with a coefficient of variation of price.

References

Apergis, N., Rezitis, A.N., 2003. Agricultural price volatility spillover effects: The case of Greece. Eur. Rev. Agric. Econ. 30(3), 389–406.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econometrics 68(1), 29–51.

Barrett, C., 1997. Liberalization and food price distributions: ARCH-M evidence from Madagascar. Food Policy 22(2), 155–173.

Bellemare, M.F., Barrett, C.B., 2006. An ordered Tobit model of market participation: Evidence from Kenya and Ethiopia. Am. J. Agric. Econ. 88(2), 324–337.

Bellemare, M.F., Masaki, T., Pepinsky, T.B., 2015. Lagged explanatory variables and the estimation of causal effects.

Berg, E., 2016. Commodity market dynamics and price volatility: Insights from dynamic storage models. Proceedings in Food System Dynamics, pp. 6–16.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econometrics 87(1), 115–143.

Bobenrieth, E., Wright, B., Zenz, D., 2013. Stocks-to-use ratios and prices as indicators of vulnerability to spikes in global cereal markets. Agric. Econ. 44, 1–10.

Branch, W.A., 2004. The theory of rationally heterogeneous expectations: Evidence from survey data on inflation expectations. Econ. J. 114(497), 592–621.

Cafiero, C., Bobenrieth, E., Bobenrieth, J., Wright, W., 2011. The empirical relevance of the competitive storage model. J. Econometrics. 162, 44–54.

Chavas, J.-P., 2000. On information and market dynamics: The case of the US beef market. J. Econ. Dyn. Control 24(5), 833–853.

De Janvry, A., Fafchamps, M., Sadoulet, E., 1991. Peasant household behaviour with missing markets: Some paradoxes explained. Econ. J. 101(409), 1400–1417.

Deaton, A., Laroque, G., 1992. On the behaviour of commodity prices. Rev. Econ. Stud. 59(1), 1–23.

Fackler, P.L., Livingston, M.J., 2002. Optimal storage by crop producers. Am. J. Agric. Econ. 84(3), 645–659.

Fafchamps, M., 1992. Cash crop production, food price volatility, and rural market integration in the third world. Am. J. Agric. Econ. 74(1), 90–99.

Femenia, F., 2015. The effects of direct storage subsidies under limited rationality: a general equilibrium analysis. Agric. Econ. 46(6), 715–728.

Frechette, D., 1999. Stock-outs and supply response estimation under rational expectations. Eur. Rev. Agric. Econ. 26(1), 59–77.

Gilbert, C., Morgan, W., 2010. Food price volatility. Philos. Trans. R. Soc. 365, 3023–3034.

Grandmont, J.-M., 1998. Expectations formation and stability of large socioeconomic systems. Econometrica. 66(4), 741–781.

Gustafson, R., 1958. Carryover levels for grains: A method for determining amounts that are optimal under specified conditions. Discussion paper, USDA.

Hommes, C., 2011. The heterogeneous expectations hypothesis: Some evidence from the lab. J. Econ. Dyn. Control. 35(1), 1–24.

Karanja, A.M., Kuyvenhoven, A., Moll, H.A., 2003. Economic reforms and evolution of producer prices in Kenya: An ARCH-M approach. Afr. Dev. Rev. 15(2–3), 271–296.

Kazianga, H., Udry, C., 2006. Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. J. Dev. Econ. 79(2), 413–446.

Key, N., Sadoulet, E., De Janvry, A., 2000. Transactions costs and agricultural household supply response. Am. J. Agric. Econ. 82(2), 245–259.

Maître d'Hôtel, E., Le Cotty, T., Jayne, T., 2013. Trade policy inconsistency and maize price volatility: An ARCH approach in Kenya. Afr. Dev. Rev. 25(4), 607–620.

Mitra, S., Boussard, J.-M., 2012. A simple model of endogenous agricultural commodity price fluctuations with storage. Agric. Econ. 43(1), 1–15.

Muth, J.F., 1961. Rational expectations and the theory of price movements. Econometrica J. Econometric Soc. 29, 315–335.

Park, A., 2009. Risk and household grain management in developing countries. Econ. J. 116(514), 1088–1115.

Peterson, H.H., Tomek, W.G., 2005. How much of commodity price behavior can a rational expectations storage model explain? Agric. Econ. 33(3), 289–303.

Saha, A., Stroud, J., 1994. A household model of on-farm storage under price risk. Am. J. Agric. Econ. 76(3), 522–534.

Serra, T., Gil, J.M., 2013. Price volatility in food markets: Can stock building mitigate price fluctuations? Eur. Rev. Agric. Econ. 40(3), 507–528.

Shively, G., 1996. Food price variability and economic reform: An ARCH approach for Ghana. Am. J. Agric. Econ. 78, 126–136.

Stephens, E.C., Barrett, C.B., 2011. Incomplete credit markets and commodity marketing behaviour. J. Agric. Econ. 62(1), 1–24.

Wright, B., 2011. The economics of grain price volatility. Appl. Econ. Perspect. Policy 33(1), 32–58.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Online appendix

Journal of African Economies, 2017, 1–30
doi: 10.1093/jae/ejx015
Article

Transport Costs and Food Price Volatility in Africa

T. Le Cotty[a,*], E. Maitre d'Hotel[a], and M. Ndiaye[b]

[a]Department of ES (Environment and Societies), CIRAD, Ouagadougou, Burkina Faso, and [b]Department of SESG (Economics, Management and Social Sciences), SUPAGRO, Montpellier, France

*Corresponding author: T. Le Cotty, CIRAD, Ouagadougou, Burkina Faso. E-mail: lecotty@cirad.fr

Abstract

We analyze the role of market remoteness on maize price volatility in a developing country, Burkina Faso. A trade model between a rural area and an urban area is used to show that transport costs increase volatility in rural markets when this volatility is due to local supply or demand shocks in the rural area. We provide empirical support to this proposition by exploring a dataset of monthly maize price series across 28 markets over the 2004–2014 period in Burkina Faso. Travel time, kilometric distance and road pavement are used as proxies for transport costs. We estimate an autoregressive conditional heteroskedasticity model to investigate the statistical effect of these proxies on maize price volatility. We find a robust and positive effect of transport costs on maize price volatility. Our findings suggest that enhancing road infrastructure in landlocked countries would strengthen the link between rural and urban markets, thereby smoothing grain price volatility.

Key words: maize, price volatility, market remoteness, transport costs, Africa

JEL classification: Q11, R32, R41

1. Introduction

High transport costs in Sub-Saharan Africa directly stem from distance and lack of quality infrastructure which reduce rural smallholders market access (Brenton, 2012, Limao and Venables, 2001), while traders from urban areas may be discouraged from purchasing food items directly from remoted farmers. It is well known that this decreases average price in supply areas but one may also want to know whether it influences price volatility. The purpose of this research is to understand how transport cost modifies price volatility in rural areas. An important factor of price volatility in Sub-Saharan Africa is the volatility transmitted from international markets (Jacks *et al.*, 2011, Minot, 2010, Rapsomanikis and Mugera, 2011). However, in countries that hardly depend on grain imports to satisfy domestic consumption, like Burkina Faso, domestic factors are more likely to explain volatility.

Trade costs include a large range of costs whose effects on international trade have been thoroughly documented (see review by Anderson and Van Wincoop, 2004). Among these costs, the relative role of transport cost in monetary terms has been decreasing, because of an increase in shipment volumes and because of the rise of new other costs like technical barriers to trade. But contrary to common wisdom and some authors' prediction (the Death of Distance, Cairncross, 1999), recent empirical evidences find a 'puzzling persistence of distance' as a major explanation of bilateral trade (Anderson and Van Wincoop, 2004, Disdier and Head, 2008, Carrere and Schiff, 2005). One reason of this persistence of the distance effect is that shipment volumes reduce monetary costs of transport but not time of transport. Time of transport makes the trade more risky because it makes transactions more uncertain (Hummels and Schaur, 2010). Furthermore, the predicted 'death of distance' is based on high-quality infrastructure, which is not the case in Africa (Limao and Venables, 2001). In Africa, the transaction risk due to transportation average time adds to a transport risk due to hazardous road quality (risk of breakdown, risk of being stuck in the mud, etc.). More than a distance effect *per se*, in this paper, we target the remoteness effect, which combines distance and infrastructures quality (see Shepherd and Wilson, 2007).

By contrast, the role of trade costs on domestic trade has not received so much attention, and the effect of domestic remoteness in particular on price behaviour has not been fully established. Several studies show the effect of trade costs on domestic trade and price, including road quality (Minten and Kyle, 1999) or traders' margins (Fafchamps, 1992, Minten and Kyle, 1999). But they do not analyse the impact of these variables on price volatility.[1] Some empirical studies explain the role of geographical domestic factors on price volatility. In particular, Kilima *et al.* (2008) establish that maize prices in Tanzania are less volatile in more developed regions, in deficit regions and in regions bordering other countries. Minot (2014) uses a sample of eleven African countries and six staple foods to show that food prices are less volatile in capital cities. This tends to indicate that prices are more volatile in remote and rural areas, but is this volatility related to transport cost ? This is the issue we address in this paper.

The intuition of what we show in this paper is related to Abdulai (2000) and Badiane and Shively (1998), who suggest that transport cost modifies price transmission between two markets. In Badiane and Shively (1998), maize price volatility occurring in local markets, in Ghana, is transmitted from central markets, and this transmission depends on transport cost. If a local market is close to the central market, price level and volatility are highly correlated with price history in the central market, and if the local market is far from the central market, price level and volatility are more correlated to price history in the local market. Their data being based on two local markets (one is integrated and close to the central market and one is less integrated and farther located), they cannot test the above assumption that differences in correlation are due to differences in transport cost. Furthermore, their purpose is to understand how a price shock in market A affects a market B, while our purpose is to understand how a shock on quantities in market A affects prices

1 In this paper as in many recent papers, we differentiate 'price variability' and 'price volatility': price variability gives an overall measure of price variation i.e. the deviation from an average or from a trend, while price volatility is defined in the literature as the unpredictable part of price variations (Engle, 1982, Bollerslev, 1986, Gilbert and Morgan, 2010). For instance, seasonality may increase price variations in surplus areas, but this is not volatility because it is a regular and predictable pattern of price variations.

in this market A, depending on transport cost between this market and a central market. Our contribution is to show that transport cost increases price volatility in rural areas when this volatility arises from local supply or demand shocks.

The paper is organised as follows. In Section 2, we introduce a simple model to explain the role of transport cost in high price volatility observed in remote rural markets. In Section 3, we present the data and some empirical features of maize production and marketing in Burkina Faso. In Section 4, we present our empirical strategy to analyze the effect of market remoteness on price volatility, based on the estimation of an autoregressive conditional heteroskedasticity model. In Section 5, we deliver our empirical results by exploring a database of maize prices in Burkina Faso on twenty-eight markets over 2004–14. We find robust evidence that maize price volatility increases with transport cost between rural and urban markets.

2. A model of transport cost and price volatility

2.1 Transport cost

The most common model of transport cost was introduced by Samuelson (1952), where price differences between two markets equal the cost of transporting the good from the low-price market (e.g. the exporting country) to the high-price market (e.g. the importing country), provided effective trade between the two regions exists. This implies that the transport cost between the importing region is not greater than the difference between the autarky price in the importing region and the autarky price in the exporting region. We apply this framework at the intra-domestic scale, where the rural area is similar to the exporting country and the urban centre is similar to the importing country. Let P^u and P^r stand for the market price in the urban and the rural markets, respectively, E is the quantity exchanged from the rural market to the urban market and T the transport cost between the two markets. We have (Samuelson, 1952)

$$\begin{aligned} P^u &= P^r + T \quad \textit{if} \qquad E > 0 \\ P^u &< P^r + T \quad \textit{if} \qquad E = 0 \end{aligned} \tag{1}$$

To add realism to our model and to fit the case of maize trade in Burkina Faso, we extend this general framework. The difference between farmgate price and the urban market price includes the transport cost per se T, and different types of costs that can be interpreted as transaction costs in a broad meaning. Transaction costs include the cost of searching information, the cost of bargaining and the cost of ensuring that the trade between markets is effectively made (Dahlman, 1979, Williamson, 1979). Whereas transport costs directly increase with remoteness, defined as the combination of distance and poor road quality, and measured either by distance or by travel time between markets, it is not obvious whether transaction costs increase with remoteness. For the purpose of our empirical analysis, we distinguish variable transaction costs (increasing with transport cost) and fixed transaction costs.

Some transaction costs may indeed increase with remoteness, like costs linked to the collection of information on stocks and prices in villages, or to the bargaining on specific transactions and to the enforcement of such sales. Collecting information on prices and stocks require more time in remote villages than in peri-urban villages, where more traders have access to reliable information on prices and stocks. As a consequence, bargaining may

take more time and energy in remote villages. Because of an oligopolistic transportation supply and warehousing supply, transaction costs may also include traders' rent. This rent is probably greater for traders who exchange with remote villages, where fewer traders compete. The market power of a more limited number of traders trading with most remote villages is obviously greater and these villages are more captive. In peri-urban villages providing grain, every consumer in the city is a potential buyer, and the oligopoly vanishes. And finally, transaction costs related to trade enforcement may be greater in remote markets also because of higher risk of breakdown and uncertainty (Francois and Manchin, 2013, Anderson and Marcouiller, 2002). This uncertainty can be formalised as acting as a hidden tax on trade, which increases with remoteness. In these examples, transaction costs increase with remoteness.

Other transaction costs do not depend on remoteness and are the same for all markets, like administration burden, for instance when trucks are submitted to domestic trade policies and controls. These costs have proven to be large in international trade (Buys *et al.*, 2010, Pomfret and Sourdin, 2010, Shepherd and Wilson, 2007), and they are probably significant at the national scale. The administrative cost is most likely identical for all markets because the controls occur on main roads around Ouagadougou, not on remote roads that make the difference in transport costs.

The trade conditions become the following, where T is transport cost per se, $V(T)$ is the sum of variable transaction costs, with $V' > 0$ and F is the sum of fixed transaction costs. Imposing a linear structure on trade costs, we have

$$\begin{aligned} P^u &= P^r + T + V(T) + F \quad \textit{if} \quad E > 0 \\ P^u &< P^r + T + V(T) + F \quad \textit{if} \quad E = 0 \end{aligned} \tag{2}$$

Although it is theoretically possible that the urban market supplies grain to the rural market, this hardly occurs in Burkina Faso, except in particular conditions of heavy food insecurity episodes where public food aid is provided to rural areas. To keep the model as simple as possible, we thus only consider the empirically most generally observed case where a rural market sells grain to an urban market.

2.2 Price shocks and price volatility

While price variability gives an overall measure of price variation, price volatility is the unpredictable part of price variation. The most appropriate indicator of volatility is probably the variance of a series of unexpected price shifts (Engle, 1982). The empirical counterpart of what price shifts are expected and what price shifts are unexpected differ among authors, but the idea that volatility is about the unpredictable price shifts is now widely accepted (Prakash, 2011, Shively, 1996, Barrett, 1997).

Nevertheless, this synthetic measure is not very convenient to understand how volatility is generated. To contribute to this understanding, Badiane and Shively (1998) concentrate on one shock and extrapolate to a succession of price shocks that produce volatility. We adopt the same approach here. We analyse the role of transport cost on the properties of one unexpected price shift occurring in a rural area (resulting from an unexpected supply shock), and we will extrapolate the outcome to the relation between transport cost and a succession of unexpected price shocks that produce volatility.

2.3 Market equilibrium

Whereas Badiane and Shively (1998) model the transmission of a price shock from one market to another, we model the conversion of a shock on quantity into a price shock as a function of market remoteness. Indeed, remoteness impacts transmission of price shocks between two markets (Roehner, 1996), and transmission of price shocks impacts the magnitude of this shock in both markets. The intuition is simple: high transport cost between market A and market B 'protects' market B from price volatility generated in market A, and amplifies price volatility in market A.

Like in the international trade model by Samuelson (1952), we call excess supply the difference between local supply and local demand in the rural market (3), and excess demand the difference between urban demand and all other sources of supply addressed to the urban market. These other sources of supply include in particular domestic rural markets apart from the one we are analyzing. Excess supply is modelled as a monthly excess supply x_t, where subscript t is a monthly index. This excess supply is a function of local price P_t^r prevailing in the rural market at month t, the stock volume S_t available in the rural area at month t, the time of the year t because sale decisions depend on the time to go until next harvest, and a monthly shock on grain availability θ_t due to unexpected events affecting local supply (rodents, fires, etc.) or local demand (disease, social events, etc.):

$$x_t(P_t^r, S_t, t, \theta_t) \tag{3}$$

Assuming no carryover, stock volume is equal to the latest yearly harvest H minus the sum of what has been sold since the latest harvest, indexed as $t = 0$:

$$S_t = H - \sum_{i=0}^{t} x_i \tag{4}$$

We introduce (3) in (4) and iteratively replace S_i in the resulting expression. Noting that $S_0 = H$ in case of no carry-over, we get an expression of $S_t(H, P_0^r, \ldots, P_t^r, t, \theta_0, \ldots, \theta_t)$. The excess supply then writes

$$x_t(H, P_0^r, P_1^r, \ldots, P_t^r, t, \theta_0, \theta_1, \ldots, \theta_t) \tag{5}$$

The monthly 'excess demand' from the urban market can be written simply $m_t(P_t^u)$ if all determinants other than price are given. The urban income is assumed to have no seasonality, and the monthly urban demand is constant during the year. It is decreasing and convex in price, $m_t' < 0$, $m_t'' > 0$.

As in Samuelson (1952), there are two market clearing conditions, depending on whether the two areas actually trade or not. The market equilibria are

$$T = P_t^u - P_t^r - V(T) - F; \quad x_t(H, P_0^r, P_1^r, \ldots, P_t^r, t, \theta_0, \theta_1, \ldots, \theta_t) = m_t(P_t^r + T + V(T) + F) \tag{6}$$

$$T > P_t^u - P_t^r - V(T) - F; \quad x_t = 0 \tag{7}$$

If $T > P_t^u - P_t^r - V(T) - F$, both prices are independent, and the trade cost has no impact on volatility in the rural market. If $T = P_t^u - P_t^r - V(T) - F$, the equilibrium

defines a market price in rural areas that depends on all exogenous variables, $P_t^{r*}(H, P_0^r, P_1^r, \ldots, P_{t-1}^r, t, \theta_0, \theta_1, \ldots, \theta_t, T, F)$. We then have two price regimes:

$$T = P_t^u - P_t^r - V(T) - F; \quad P_t^r = P_t^{r*}(H, P_0^r, P_1^r, \ldots, P_{t-1}^r, t, \theta_0, \theta_1, \ldots, \theta_t, T, F) \tag{8}$$

$$T > P_t^u - P_t^r - V(T) - F; \quad P_t^r = P_t^r(H, P_0^r, P_1^r, \ldots, P_{t-1}^r, t, \theta_0, \theta_1, \ldots, \theta_t) \tag{9}$$

2.4 Comparative statics in a connected market

Totally differentiating equation (6) leads to

$$\begin{aligned} \mathrm{d}P_t^r = &- \frac{\frac{\partial x_t}{\partial H}}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}H - \frac{\frac{\partial x_t}{\partial \theta_t}}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}\theta_t + \frac{m_t'(1+V')}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}T + \frac{m_t'}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}F - \frac{\frac{\partial x_t}{\partial t}}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}t \\ &- \sum_{i=0}^{t-1} \frac{\frac{\partial x_t}{\partial P_i^r}}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}P_i^r - \sum_{i=0}^{t-1} \frac{\frac{\partial x_t}{\partial \theta_i^r}}{\frac{\partial x_t}{\partial P_t} - m_t'}\mathrm{d}\theta_i^r \end{aligned} \tag{10}$$

The first term in equation (10) is positive since m_t' is negative and tells that market price at any time of the year is lower when harvest is important.

The second term tells that a positive shock on excess supply $\frac{\partial x_t}{\partial \theta_t}$ produces an unexpected decrease in price. This decrease is all the larger as the excess supply and the excess demand are inelastic, i.e. $\frac{\partial x_t}{\partial P_t} \to 0$ and $m_t' \to 0$. Since this shock is by definition unexpected, the price shift is itself unexpected. Thus, successive unexpected shocks on excess supply produce a series of unexpected price shifts, which fuel rural price volatility.

The third term is negative and confirms that the price in the rural area decreases with transport cost. Naturally, this price drop is all the sharper as variable transaction costs increase with remoteness, i.e. V' is large.

The fourth term accounts for the price drop as fixed transaction costs increase. The fifth term accounts for seasonality. For any type of time preferences with positive discount rate, farmers with no liquidity and no carry-over sell more grain in the first month after harvest, a bit less in the second month, etc. This is why we generally observe that sales decrease with time $\frac{\partial x_t}{\partial t} < 0$, which produces a increasing trend in price from the harvest to the lean season. Price seasonality is often described as a succession of two main seasons: (i) the harvest season, characterised by the abundance of products on markets, high excess supply and low prices and (ii) the lean season, featuring product scarcity, low monthly excess supply and high grain prices. The continuous counterpart of it is the progressive stock decrease described above.

The sixth term is positive since $\frac{\partial x_t}{\partial P_i^r} < 0$; $i < t$: if past prices have been high, farmers have sold more and sell less now, so that present price is all the greater as it has been high in the recent past. It is a main reason for rural prices being positively autocorrelated.

And finally, the last term indicates that positive past supply shocks have a negative effect on the current price, due to a lower current supply.

2.5 Comparative statics in a disconnected market

If there is no trade between the two markets, equation (7) is derived and produces

$$\mathrm{d}P_t^r = -\frac{\frac{\partial x_t}{\partial H}}{\frac{\partial x_t}{\partial P_t}}\mathrm{d}H - \frac{\frac{\partial x_t}{\partial \theta_t}}{\frac{\partial x_t}{\partial P_t}}\mathrm{d}\theta_t - \frac{\frac{\partial x_t}{\partial t}}{\frac{\partial x_t}{\partial P_t}}\mathrm{d}t - \sum_{i=0}^{t-1}\frac{\frac{\partial x_t}{\partial P_t^r}}{\frac{\partial x_t}{\partial P_t}}\mathrm{d}P_t^r - \sum_{i=0}^{t-1}\frac{\frac{\partial x_t}{\partial \theta_t^r}}{\frac{\partial x_t}{\partial P_t}}\mathrm{d}\theta_t^r \tag{11}$$

Comparing second terms of equations (10) and (11) directly shows that supply shocks have a greater impact on local prices in the disconnected market (smaller denominator of the second term).

Supply and demand shocks in a rural disconnected area produce price shocks in this area that are greater than in a rural area connected to an urban market for equivalent local or demand shocks. Since the variance of these shocks increases with their magnitude (for a same frequency), it is greater in a disconnected area. Since these shocks are unexpected (the variance of unexpected price shocks being the volatility), price volatility is greater in disconnected areas.

2.6 Volatility in the case of many interconnected and disconnected markets

In reality, many interconnected and disconnected markets operate simultaneously, and at each period, a price drop in a disconnected market can reconnect this market to the urban market and conversely a single price rise in a connected market can disconnect it. All connected markets have parallel price patterns by equation (1) while they are connected, and disconnected markets have their own price pattern, while they are disconnected. While they are connected, price volatility is the same in all markets, and while they are disconnected, volatility is different. Subsequently, changes in price regime (connection–disconnection) produce changes in volatility.

Comparison between equations (10) and (11) also makes it clear that unexpected prices shocks in rural markets θ_t^r have a greater impact on rural price in disconnected market $\left|\frac{\partial P_t^r}{\partial \theta_t}\right| = \left|\frac{\frac{\partial x_t}{\partial \theta_t}}{\frac{\partial x_t}{\partial P_t}}\right|$ than in connected market, $\left|\frac{\partial P_t^r}{\partial \theta_t}\right| = \left|\frac{\frac{\partial x_t}{\partial \theta_t}}{\frac{\partial x_t}{\partial P_t} - m_t'}\right|$. Since $\mathrm{prob}(x_t = 0) = \mathrm{prob}(T > P_t^u - P_t^r - V(T) - F)$, and since this probability increases with T, $\mathrm{prob}\left(\left|\frac{\partial P_t^r}{\partial \theta_t}\right| = \left|\frac{\frac{\partial x_t}{\partial \theta_t}}{\frac{\partial x_t}{\partial P_t}}\right|\right)$ increases with T. This proves that the magnitude of unexpected price shocks is greater when T is greater.

Proposition *When rural market volatility is due to local supply or local demand shocks, the magnitude of unexpected price shocks in this market increases with transport cost between this market and related consumption markets.*

3. Maize in Burkina Faso: data and trends

3.1 Maize production in Burkina Faso

In Burkina Faso, agriculture employs around 85% of the population and contributes to 34% of gross domestic product. Maize is the second cereal produced in Burkina Faso with around 1,500,000 metric tonnes produced, after sorghum. Maize production has significantly increased in the last decade, rising at a faster pace than sorghum, millet and rice (see Figure 6 in the Appendix).

While most of millet and sorghum production tends to be consumed by farmers, maize is mostly sold on markets. Thus, maize is one of the main sources of agricultural income in

Burkina Faso, ranking second after cotton. Maize production is mostly located in the western and southern parts of the country, where pedo-climatic conditions are more favourable. Maize is mainly traded within the country, flowing from maize-surplus to maize-deficit regions. Depending on the level of national production, small amounts of maize exports can be recorded towards Niger and Mali[2]), and even smaller imports can be imported from Côte d'Ivoire, Ghana and Togo.[3] We can consider Burkina Faso as a self-sufficient country for maize (this is not the case for rice, most of the rice consumed being imported).

3.2 Maize prices in Burkina Faso

Our analysis relies on historical price data collected by the public institution SONAGESS (Société Nationale de Gestion du Stock Alimentaire). SONAGESS manages its own market information system since 1992. Prices of main agricultural commodities are collected weekly on 48 markets, and price averages are computed monthly. One different agent is responsible for each market and collects price observed on the market once a week. This may be any day of the week, depending on the village or the city market day. The fact that SONAGESS provides monthly average means that our data do not account for the high-frequency volatility. We measure only inter-month fluctuations. Furthermore, averaging weekly prices tends to smoothen the monthly price as compared with monthly prices collected once a month (Brunt and Cannon, 2014).

We analyze twenty-eight markets with monthly data over the July 2004–November 2013 period. We set aside markets for which price series present discontinuities. For each market, monthly maize price series are expressed in local currency per kilogram (FCFA/kg) and then deflated by the Consumer Price Index of Burkina Faso (2008 base 100) published monthly by the INSD (National Institute of Statistics and Demography).

In Burkina Faso, maize prices are relatively disconnected from international prices because of very low quantities of maize traded with partner countries. A cointegration test between international and average national maize price series in Burkina Faso indicates that there is no long run equilibrium relation tying international and national maize prices together and thus confirms this disconnection (see Table 6 in the Appendix).

Markets are located either in surplus areas, i.e. where maize production exceeds consumption or in deficit areas, i.e. where maize production is not enough to cover maize consumption. We used production, consumption and demographic data to evaluate the difference between production and consumption at the regional levels (thirteen regions). Regional production data were obtained from the Burkina Faso CountryStat database, regional demographic data were obtained from the INSD and maize per capita average annual consumption was approximated of 108 kg/capita/ year.[4]

Figure 1 displays the evolution of maize real prices in a remote market situated in a deficit area (Dori), in a remote market situated in a surplus area (Solenzo) and in a market of the capital city (Sankaryare, Ouagadougou).

2 25,000 metric tons of maize were exported from Burkina Faso in 2013, representing less than 2% of the domestic production, FAOSTAT data downloaded on 26 August 2015.

3 5000 metric tons of maize were imported in Burkina Faso in 2013, FAOSTAT data downloaded on August 2015.

4 This proxy was obtained by the partners of the Farm Risk Management in Africa project (www.farmaf.org) who conducted 1500 rural households surveys in Burkina Faso in 2013.

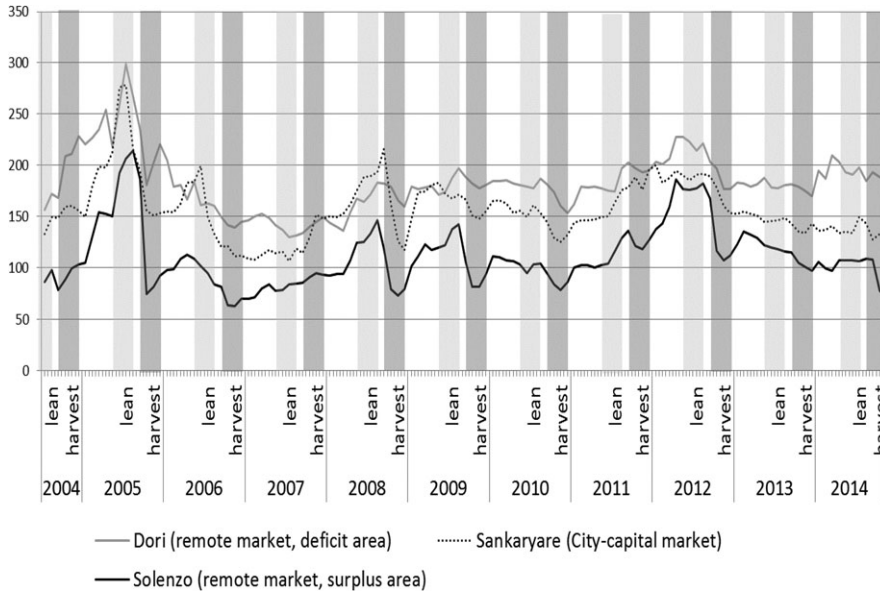


Figure 1: Maize real prices evolution in Dori, Solenzo and Sankaryare markets (FCFA/kg).

In these three markets (and more generally in the twenty-eight markets studied), the price patterns present similarities. First, prices are strongly affected by seasonal patterns: they are lower in the harvest season that begins in September/October and higher in the lean period that happens from June to August. Second, interannual variations also have common features. For instance, the price spike in 2005 due to grasshopper invasion during 2004 campaign is observed everywhere in the country, so is the 2008 spike due to drought during 2007 campaign and international crisis.

Nevertheless, clear differences in price patterns can be seen. Price patterns in Sankaryare and Solenzo are quite parallel most of the time, and the constant difference between the two prices could be the transport cost between the two areas.[5] Nevertheless, in two occasions of grain shortage, 2005 and 2012, the price increased more sharply in Solenzo and almost reached the same price as in Sankaryare. These facts are compatible with the above theory in case of price disconnection episodes. The price spike in Solenzo is such that the price in Solenzo plus transport cost exceeds the price in Sankaryare when Sankaryare stops purchasing maize from Solenzo and purchases more maize from other areas. This smoothens the price spike in Sankaryare and increases spike in Solenzo.

The price pattern in Dori is quite different. Since Dori is a deficit rural area, it is not surprising that price is often higher in Dori than in Sankaryare. It is easy to see that the difference between the two prices varies constantly. The reason is simply that prices are not

5 An average transport cost of 40 FCFA/kg between Solenzo and Sankaryare is expensive, but not unlikely. It means a unit cost of 274 FCFA/km per tonne, whereas in Niger reported net unit transport costs per tonne per km are 60 FCFA. Since gross transport cost includes the monetary and the opportunity cost of fixing truck, which is often higher than the net cost of transportation, we find the unit cost of 274 FCFA per tonne per km plausible.

connected in the sense of the above theory. The price in the rural area is almost all the time higher than the price in urban area minus transport cost, and the two areas do not trade grain. The reason why prices patterns are somehow similar (high at the same periods and low at the same periods) is because both areas are connected to rural areas that face similar supply shocks (drought affects more or less all suppliers).

4. Empirical strategy

We test the effect of transport costs on price volatility. To do so, we use a monthly panel regression of twenty-eight markets to estimate the average effect of transport costs on average maize price volatility. Price volatility is defined as the unpredictable component of price fluctuations (Prakash, 2011). Appropriate models to measure volatility are ARCH family models (for AutoRegressive Conditional Heteroskedasticity), in which the variance of residuals is allowed to depend on the most recent residuals and other variables. This variance is generally considered as a good measure of volatility.

4.1 ARCH models

ARCH models were introduced by Engle (1982) and generalised by Bollerslev (1986). They have extensively been used to study price volatility of agricultural products (Beck, 1993, Shively, 1996, Barrett, 1997, Kilima *et al.*, 2008, Maître d'Hôtel *et al.*, 2013). A reason is that they can be interpreted as a measure of what is predictable in price variation (the mean equation) and a measure of what is unpredictable in price variations (the variance equation). Furthermore, in the ARCH model, the conditional variance depends on the lagged squared residuals of the mean equation. Therefore, the measure of volatility varies with time, which can be used to understand changes in volatility. And by including additional regressors in the variance equation, the model can be used to identify potential determinants of price volatility.

The structure of ARCH models is made of two simultaneous equations: the first equation is the price forecast one and the second is the conditional variance one. In the second equation, the conditional variance of the residuals of the first equation typically measures the unpredictable price shifts and is thus used as an indicator of price volatility.

The typical ARCH(p) structure to describe price formation in a particular market place is given by the following equations:

$$P_t = a_0 + \sum_{i=1}^{j} a_i P_{t-i} + bX_t + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, h_t) \tag{12}$$

$$h_t = c_0 + \sum_{i=1}^{p} c_i \varepsilon_{t-i}^2 + \sum_{i=1}^{j} d_i P_{t-i} + eZ_t + \nu_t, \qquad \nu_t \sim \mathcal{N}(0, \sigma) \tag{13}$$

where t is a monthly time index, P_t is the price at month t, P_{t-i} for $i \in [1, \ldots, p]$ are lagged prices, index j is for the last significant autoregressive period; ε_t is the error term, h_t is the time-dependent variance of the error and X and Z are two column vectors of exogenous variables like international prices or seasonal dummies.

4.2 Model specification

We use a panel of twenty-eight time series corresponding to twenty-eight market places and 125 cross sections corresponding to 10 years of monthly observations. The effect of transport costs on price level is interpreted from the first equation of the ARCH model, and the effect on volatility is interpreted from the second equation.

4.2.1 First set of estimations: a common price dynamics

In a first set of estimations, the following two ARCH equations are estimated jointly:

$$\begin{aligned} P_{it} = {} & \gamma_0 + \gamma_1 P_{it-1} + \gamma_2 IP_t + \gamma_3 ER_t + \gamma_4 HARVEST_t + \gamma_5 LEAN_t + \gamma_6 BORDER_i \\ & + \gamma_7 TRANSPORT_i + \gamma_8 TREND_t + \gamma_9 RAINFALL_i + \sum_1^3 \eta_k REGION_k \\ & + \sum_1^9 \sigma_k ETHNY_k + \sum_{j=1}^{27} \Delta_j M_j + \varepsilon_{it}, \qquad \varepsilon_{it} \sim \mathcal{N}(0, h_{it}) \end{aligned} \tag{14}$$

$$\begin{aligned} h_{it} = {} & \varphi_0 + \varphi_1 \varepsilon_{it-1}^2 + \varphi_2 P_{it-1} + \varphi_3 IP_t + \varphi_4 ER_t + \varphi_5 HARVEST_t + \varphi_6 LEAN_t + \varphi_7 BORDER_i \\ & + \varphi_8 TRANSPORT_i + \varphi_9 TREND_t + \varphi_{10} RAINFALL_t + \sum_1^3 \chi_k REGION_k \\ & + \sum_1^9 \phi_k ETHNY_k + \sum_{j=1}^{27} \rho_j M_j + \nu_{it}, \qquad \nu_{it} \sim \mathcal{N}(0, \sigma) \end{aligned} \tag{15}$$

where P_{it} is the real maize price in market i at month t, IP_t is the real international maize price at month t, ER_t is the nominal exchange rate at month t, $HARVEST_t$ is a seasonal dummy that indicates the harvest season (October–December), $LEAN_t$ is a dummy that indicates the lean season (June–August), $BORDER_i$ is the travel time between the market i and the nearest cross-border maize point with Ghana, Côte d'Ivoire, or Togo, $TRANSPORT_i$ is the transport cost between the market i and Ouagadougou (and as robustness tests, between the market i and the nearest city and between the market i and the remaining markets), $TREND_t$ is a monthly trend, $RAINFAL_i$ is the annual average rainfall in the area where market i is located, $REGION_k$ is a regional dummy for each of the four climatic zones (Sahelian, South Sahelian, Soudanian and South Soudanien), $ETHNY_k$ is a dummy for the market located in one of the ten dominant ethnic groups (see map below), M_i denotes maize market dummy variables and ε_{it} is the heteroscedastic error term (Figures 2 and 3). The market-specific variables and the regional variables are to reflect heterogeneity in markets price dynamics that is not due to remoteness. The localisation of the four climatic zones and the ten ethnic groups is depicted in Figures 2 and 3 in the Appendix.

Coefficients γ_7 and φ_8, which we are particularly interested in, include the direct effect of transport cost on rural price, and the indirect effects of transport cost through the effect of variable transaction costs on rural price. As we have seen, both effects have the same negative sign. The size of the coefficient should then be interpreted cautiously, but the expected sign is not ambiguous. The effect of fixed transaction costs on price is included in the constant terms γ_0 and φ_0, since fixed costs are supposedly the same for every market. If it is not the case, for instance because these unobserved fixed transaction costs are market specific, they could potentially produce a bias of omitted variables. Nevertheless, the panel structure allows us to estimate fixed effects to capture some unobserved heterogeneity, including latter costs. Fixed

Figure 2: Climatic zones in Burkina Faso.
Source: http://ornithologieetbetta.free.fr/ornitho/ornitho_burkina_pays.php.

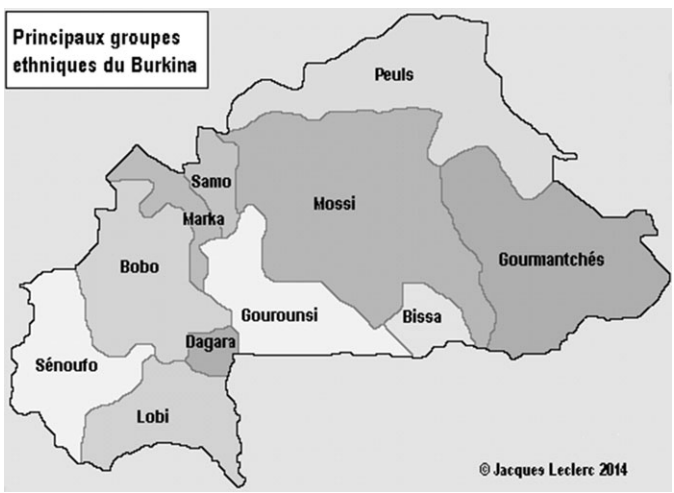


Figure 3: Ethnic groups in Burkina Faso.
Source: http://www.axl.cefan.ulaval.ca/afrique/burkina.htm.

effects are not compatible with the introduction of explicit fixed geographical variables since fixed effects include all geographical fixed effects, so that we show results of both strategies.

Monthly nominal maize prices obtained from SONAGESS were deflated with the monthly Burkinabe Consumer Price Index obtained from INSD. Monthly nominal exchange rates were obtained from the International Monetary Fund database. Nominal international price (US Gulf No. 2, yellow), obtained from the International Monetary Fund database, has been converted into FCFA and deflated using the monthly Burkinabe Consumer Price Index obtained from INSD.

The variable $TRANSPORT_i$ synthesises the sum of costs of transporting grain from the rural market i to the main urban centre that actually or potentially purchases this grain. The travel time and the kilometric distance to a main urban centre or a major market are the most commonly used measures (Barrett, 1996, Minten and Kyle, 1999, Stifel and Minten, 2008, Minot, 2014). The quality of road infrastructure can be alternatively used to have a more accurate measure of travel costs, especially in countries with poor road infrastructure (Minten and Randrianarison, 2003). In our first set of estimations, we took Ouagadougou, the capital city of Burkina Faso, with a population of around 2 million inhabitants, as the urban centre for all markets. Three proxies are used to measure the transport cost: (i) the TRAVEL TIME needed from the rural market to reach Ouagadougou, (ii) the kilometric DISTANCE between the market and Ouagadougou and (iii) a dummy variable indicating if the market is accessible with an UNPAVED ROAD or not (see Figure 4). To compute information on travel time and kilometric distance, we extracted information from the route planning application of Google Maps desktop service. To compute information on road pavement, we use the road map of Burkina Faso published in 2009 map by the Geographical Institute of Burkina Faso where paved road and unpaved roads are identified.

It could be that the most relevant urban centre for each market may differ from Ouagadougou, because of its closest location and its relative activity size. It could be also, especially if we consider that trade is a network, that remoteness should not be defined as a distance to a single reference location. For these two reasons, we led two additional estimations based on two different measures of remoteness (the results are presented in the Robustness tests section). First, we chose three main cities, namely Ouagadougou, Bobo-Dioulasso and Koudougou as relevant urban centre to define remoteness and constructed a *TIME_TO_CLOSEST_CITY* variable. Bobo-Dioulasso is the second major city, with an estimated population of 500,000 inhabitants, and Koudougou is the third city with a population around 100,000 inhabitants. Ouagadougou and Bobo-Dioulasso are growing fast, with population growth rate estimated at, respectively, 7.6% and 7.2%. Second, we constructed the variable *CUMULATIVE_TIME* to compute, for each market, the sum of its time travel time to all other twenty-seven markets.

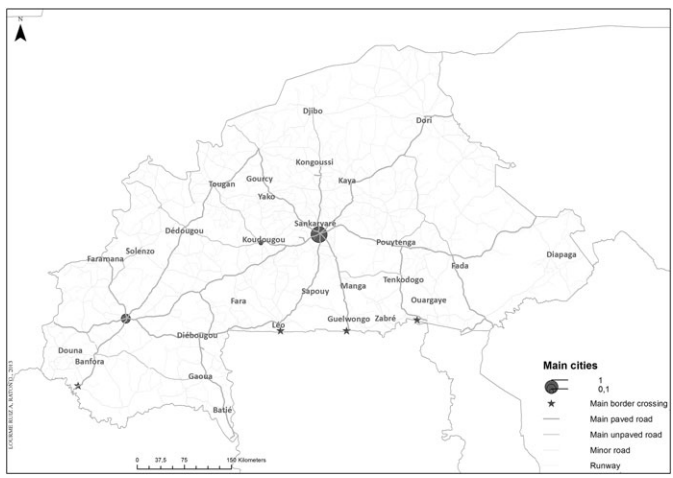


Figure 4: Maize markets localisation in Burkina Faso.

For the definition of the *BORDER* variable, we have considered the four main border points in terms of maize trade volumes, and consequently estimated the travel time from the twenty-eight markets to the nearest border point. Relying on relatively scarce data we had from the CountryStat database on the volume of maize traded, we identified four major maize border-crossing points among eighteen: Bittou (Togo), Dakola (Ghana), Leo (Ghana) and Niangoloko (Côte d'Ivoire). The reported trade amounts are very low (respectively, 9 tonnes, 8 tonnes, 1 tonne and 5 tonnes for 2002), suggesting that maize may be traded informally between Burkina Faso and its southern neighbours. Descriptive statistics of all the variables used in our study are presented in Table 8 in the Appendix.

The *ETHNY* variable is introduced to check whether belonging to an ethnic group may rend the negotiation tougher for instance (Aker *et al.*, 2014). The *REGION* variable may also influence price, and also the transport cost itself during the rainy season. The *RAINFALL* variable tests the same idea more directly, since it is a continuous variable.

The order of the ARCH model is determined through an assessment of the statistical significance generated from the Lagrange multiplier test. Results suggest that the price process is correctly described by an autoregressive order of one, *ARCH*(1).

The system of equations (14) and (15) is estimated with maximum likelihood estimation. Before starting the estimations, maize price series, the dependent variable, was tested for stationarity. The Augmented Dickey Fuller (ADF) test for panel was applied to test the null hypothesis of the presence of unit roots, following Im *et al.* (2003). The panel unit root test leads to reject the null hypothesis of non-stationarity at the 5% level.

Existing tests for cross-sectional dependences (Pesaran, 2007, Pesaran *et al.*, 2013, Kapetanios *et al.*, 2014, Driscoll and Kraay, 1998) require an unconditional variance of the error term. Because of the existence of possible bias due to cross-sectional dependences, we develop a second set of estimation below, where cross-sectional dependence can be tested and corrected for through Driscoll and Kraay standard error correction.

4.2.2 Second set of estimations: market-specific price dynamics

In above estimation, we make the assumption that price dynamics are similar in all markets and can be correctly described by a single ARCH(1) model: we estimate average coefficients. Indeed, coefficients γ_0, γ_1, etc. are the same for all markets. However, price dynamics may differ from one market to one another and we may find it more appropriate to estimate coefficients that are specific to each market. Thus, we develop a set of estimations where in a first step we estimate separately the price dynamics with twenty-eight time series and we extract the corresponding twenty-eight series of volatility and in a second step we regress those volatility series with independent variables in a panel setting. Before starting the estimations, the twenty-eight maize price series were tested for stationarity with the classic ADF test: twenty-seven markets presented stationary price patterns at the 10% level, while prices in the remaining market could be considered stationary at the 15% level. The estimation of twenty-eight ARCH models revealed that in twenty-six of the markets, prices dynamics were correctly described with an autoregressive order of one, while the model failed to converge in two of the markets that were excluded from the panel regression.

The estimation procedure has two steps. We first estimate separately ARCH model below for each market, equations (16) and (17), where the γ's and the φ's are now market specific (indexed by i). We store the series of variances h_{it} and use them as the endogenous variable of a panel model (equation (18)), which yields average coefficients as in the previous procedure. In this procedure, heterogeneity in volatility between markets come both

from different variable values (P_{it-1}, $BORDER_i$, $TRANSPORT_i$) and different coefficients, accounting for market specific effects of these variables.

For $i = 1$–28, we estimate

$$P_{it} = \gamma_{0,i} + \gamma_{1,i}P_{it-1} + \gamma_{2,i}IP_t + \gamma_{3,i}ER_t + \gamma_{4,i}HARVEST_t + \gamma_{5,i}LEAN_t + \gamma_{8,i}TREND_t + \varepsilon_{it}, \qquad \varepsilon_{it} \sim \mathcal{N}(0, h_{it}) \tag{16}$$

$$h_{it} = \varphi_{0,i} + \varphi_{1,i}\varepsilon_{it-1}^2 + \nu_{it}, \qquad \nu_{it} \sim \mathcal{N}(0, \sigma_i) \tag{17}$$

and then we build the panel

$$h_{it} = \beta_0 + \beta_1\varepsilon_{it-1}^2 + \beta_2 P_{it-1} + \beta_3 IP_t + \beta_4 ER_t + \beta_5 HARVEST_t + \beta_6 LEAN_t + \beta_7 BORDER_i + \beta_8 TRANSPORT_i + \beta_9 TREND_t + \beta_{10} RAINFALL_t + \sum_1^3 \alpha_k REGION_k + \sum_1^9 \psi_k ETHNY_k + \sum_{j=1}^{27} \delta_j M_j + \nu_{it}, \qquad \nu_{it} \sim \mathcal{N}(0, \sigma) \tag{18}$$

Both Driscoll and Kraay's and Pesaran's test show cross-sectional correlation. Driscoll and Kraay (1998) propose a non-parametric covariance matrix estimator that produces heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of cross-sectional and temporal dependence. It is in particular compatible with fixed effects panel estimation. We provide below panel estimates with this Driscoll and Kraay standard errors correction. It comes out that the cross-sectional dependence does not alter the sign and significance of the effects of variables at the core of the paper.

Our analysis, like virtually all existing GARCH and ARCH empirical models in the literature, is subject to the caveat that we have to assume weak cross-sectional dependence across the panel: we have employed Driscoll and Kraay standard errors to address weak dependence, but our strategy fails if cross-sectional dependence is of the strong type such as that arising from a common factor model. To the best of our knowledge, there is at present no convenient remedy available in the literature.

4.3 Predicted effects

The effect of transport cost between rural market and urban market on average price in the rural market is summarised by the coefficient γ_7 in equation (14). In accordance with equation (10), we expect maize prices to be lower in remote markets than in markets located close to the urban centre, i.e. $\gamma_7 < 0$. The effect of transport cost on volatility in the rural market is summarised by φ_8 in equation (15) and β_8 in equation (18). According to our proposition, we expect remote markets to exhibit greater maize price volatility than markets located close to the urban centre, i.e. $\varphi_8 > 0$ and $\beta_8 > 0$.

5. Empirical results

Results from a common ARCH model are found in Table 1 for the three different proxies of transport cost. In each one of the three specifications, the first column lists estimates of the mean equation and the second column lists estimates of the variance equation. Thus,

Table 1: Effect of Transport Costs on Maize Price Volatility: Common Price Dynamics

	[1]		[2]		[3]		[4]		[5]		[6]		[7]	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	33.88***	12.09	30.80*	−81.49***	35.67***	−84.34*	34.19***	174.17***	45.55***	209.19***	33.41***	−100.95**	33.22***	49.16
	(0.000)	(0.783)	(0.000)	(0.075)	(0.000)	(0.060)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.213)
Arch term		0.15***		0.15***		0.16***		0.21***		0.24***		0.16***		0.14***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Lagged price	0.88***	1.15***	0.87***	0.51***	0.87***	0.57***	0.85***	0.47***	0.83***	0.29***	0.92***	1.54***	0.91***	1.54***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
International price	0.05***	−0.75***	0.06***	−0.55***	0.06***	−0.58***	0.06***	−0.31***	0.05**	−0.19**	0.04***	−0.61	0.04***	−0.61***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.144)	(0.000)	(0.000)
Exchange rate	−0.03***	0.15*	−0.03***	0.50***	−0.04***	0.51***	−0.03***	−0.07	−0.03***	−0.04	−0.03***	0.11***	−0.03***	−0.02
	(0.000)	(0.087)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.352)	(0.000)	(0.423)	(0.000)	(0.000)	(0.000)	(0.739)
Harvest dummy	−6.37***	132.71***	−6.76***	140.99***	−6.75***	142.60***	−6.51***	113.72***	−6.59***	76.46***	−5.95***	126.20***	−6.09***	118.25***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	1.92***	0.03*	1.90***	−2.59	1.97***	−2.38	1.40***	−2.90	1.57***	−4.39*	1.18***	−1.50	1.00***	−0.56
	(0.000)	(0.992)	(0.000)	(0.439)	(0.000)	(0.517	(0.000)	(0.129)	(0.000)	(0.076)	(0.004)	(0.586)	(0.009)	(0.827)
Time to the border	0.01***	−0.16***	0.04***	−0.00	0.01**	0.04**	0.01***	0.12***	0.04***	0.03	0.01*	−0.17***	0.01	−0.42***
	(0.005)	(0.000)	(0.000)	(0.910)	(0.000)	(0.013)	(0.004)	(0.002)	(0.000)	(0.656)	(0.054)	(0.000)	(0.314)	(0.000)
Time to Ouaga	−0.01***	0.21***					−0.01***	0.09***	−0.01***	0.11***	−0.01***	0.25***	−0.01**	0.38***
	(0.000)	(0.000)					(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.000)	(0.029)	(0.000)
Distance to Ouaga			−0.03***	0.18***										
			(0.000)	(0.000)									)	
Unpaved road					−6.35***	16.86***								
					(0.000)	(0.000)								
Trend	−0.06***	−1.05***	−0.06***	−1.33***	−0.06***	−1.29***	−0.05***	−1.45***	−0.05***	−1.54***	−0.05***	−1.04***	−0.05***	−1.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	NO	YES	NO	YES	NO	YES	YES	YES	YES	NO	NO	NO	NO
Annual rainfall									−0.01***	−0.01				
									(0.005)	(0.575)				
South Sahelian climate											−2.16**	43.18***		
											(0.013)	(0.000)		
North Soudanian climate											−2.88***	73.41***		
											(0.001)	(0.000)		

South Soudanian climate						−2.50**	28.19**	
						(0.015)	(0.005)	
Peulh ethny								2.90**	−33.19***
								(0.011)	(0.003)
Gourmantche ethny								0.65	60.05***
								(0.656)	(0.000)
Bissa ethny								−0.55	−33.20***
								(0.686)	(0.008)
Lobi ethny								2.94*	−22.74
								(0.066)	(0.140)
Senoufo ethny								−0.83	−86.91***
								(0.650)	(0.000)
Dagara ethny								−1.63	−31.50***
								(0.130)	(0.001)
Bobo ethny								−1.14	−6.78
								(0.358)	(0.480)
Gourounsi ethny								−1.03	0.94
								(0.415)	(0.932)
Mossi ethny								−0.27	11.27
								(0.803)	(0.254)
N	3472	3472	3472	3472	3472	3472		3472	
R squared	0.8362	0.8370	0.8371	0.8370	0.8377	0.8311		0.8327	

p-values in brackets.
*Significant at 10%; **significant at 5%; ***significant at 1%.
[1] Travel time to Ouagadougou.
Kilometric distance to Ouagadougou.
[3] Road pavement.
[4] Market dummies.
[5] Rainfall and market dummies.
[6] Climatic zone dummies.
[7] Ethnic group dummies.

for each specification, price effects of exogenous variables are in the first column, and volatility effects of exogenous variables are in second column.

Results from a panel that allows for differences in price dynamics in each market and for cross-sectional interactions are presented in Table 2.

5.1 Rural price drivers

In this subsection, we discuss the results presented in Tables 1 and 2. There is a strong autocorrelation in monthly price series and we can see in Tables 1 and 2 that on average, a 10 FCFA increase in maize price on a market contributes to a 9 FCFA increase in maize price the following month. The negative trend reveals that on average, the level of maize prices has decreased over the 10 years period. As expected, the seasonal dummies reveal that prices are significantly higher during the lean season and lower during the harvest season. On average, maize prices decrease by 6 or 7 FCFA in the harvest season ranging from October to December and increase by 1 or 2 FCFA in the lean season ranging from June to August.

We find a significant positive effect of maize international prices on domestic prices patterns, with a rather low coefficient however, a 10 FCFA increase in international price leading to a 0.5 FCFA increase in domestic prices. This confirms the relative disconnection between international markets and domestic markets in Burkina Faso, in line with the cointegration tests presented in the Appendix. This suggests that maize prices are mostly driven by domestic factors in Burkina Faso, a landlocked country with very low grain imports levels.

Prices are lower in remote markets, this effect being robust to the three proxies used for transport costs (Table 1) and to the inclusion of climatic and ethnic control variables (Table 2). An increase of 1 min in travel time to the capital city produces a decrease of 0.01 FCFA in prices, and an increase of 1 km of distance from the capital city produces a 0.03 FCFA decrease in prices. Prices in markets accessible by unpaved roads are on average lower by 6 FCFA/kg than those prevailing in markets accessible by paved roads. This negative effect of transport costs on the level of prices is expected in the theoretical model. Symmetrically, food price increases as one gets closer to urban areas.

When markets are more distant from the border of Côte d'Ivoire, Ghana and Togo, prices are higher. This effect is probably due to the more favourable climatic conditions in these countries that decrease production costs, and makes harvest earlier, especially in Ghana, which foster trade between neighbour countries and drives prices down in surrounding markets.

From Tables 1 and 2, we interpret that rainfall has a decreasing effect on price levels: prices are lower in rainy areas, where maize production is more important than in dry areas. The same effect is revealed by the climatic dummies: four climatic zones are identified, from the driest one to the wettest one: North Sahelian, South Sahelian, North Soudanian and South Soudanian. The North Sahelian dummy was dropped in the results indicating that the results have to be interpreted in comparison with this zone, which is the driest of Burkina Faso (the northernmost actually). Prices tend to be lower in South Sahelian, North Soudanian and South Soudanian zones than in North Sahelian zone where maize production is scarce, and where prices are higher.

The only ethnic group variable that does have a significant effect on price levels is the peulh ethnic group, primarily located at the northernmost area of Burkina Faso, and whose

Table 2: Effect of Transport Costs on Maize Price Volatility: Market-Specific Price Dynamics

	[8]	[9]	[10]	[11]
Lagged price	3.050***	3.050***	2.836***	2.784***
	(0.000)	(0.000)	(0.000)	(0.000)
International price	−0.728	−0.728	−0.513	−0.545
	(0.206)	(0.206)	(0.407)	(0.374)
Exchange rate	1.320***	1.320***	1.351***	1.386***
	(0.001)	(0.001)	(0.001)	(0.001)
Harvest dummy	64.49***	64.49***	64.93***	64.74***
	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	14.17	14.17	10.52	14.76
	(0.376)	(0.376)	(0.520)	(0.373)
Time to the border	−0.127	1.921***	0.0932	−0.539***
	(0.909)	(0.005)	(0.328)	(0.000)
Time to Ouagadougou	1.029**	0.991***	0.428***	0.412*
	(0.011)	(0.001)	(0.000)	(0.056)
Trend	−2.172***	−2.172***	−2.119***	−2.158***
	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	YES	NO	NO
Annual rainfall		−1.172***		
		(0.000)		
Sahelian climate			−132.8***	
			(0.000)	
South Sahelian climate			16.11	
			(0.698)	
North Soudanian climate			123.6***	
			(0.000)	
Peulh ethny				−141.1***
				(0.000)
Gourmantche ethny				−0.735
				(0.979)
Bissa ethny				−33.44
				(0.114)
Lobi ethny				−24.51
				(0.749)
Senoufo ethny				−157.6***
				(0.004)
Dagara ethny				−2.074
				(0.982)
Samo ethny				−51.73
				(0.243)
Bobo ethny				138.3***
				(0.008)
Gourounsi ethny				−10.57
				(0.609)

Continued

Table 2: Continued

	[8]	[9]	[10]	[11]
Mossi ethny				0
				(.)
_cons	−576.9**	0	−813.3***	−648.4***
	(−2.24)	(.)	(−3.64)	(−2.93)
N	3224	3224	3224	3224
Wald Chi^2	640	843	486	505

p-values in brackets.
*Significant at 10%; **significant at 5%; ***significant at 1%.
[8] Market dummies.
[9] Rainfall and market dummies.
[10] Climatic zone dummies.
[11] Ethnic group dummies.

activity is oriented towards cattle breeding rather than maize growing. Given the dry climate and the peulh culture, it is thus rather intuitive that maize prices are higher in the northern parts of Burkina Faso.

5.2 Rural volatility drivers

The ARCH(1) term is positive and significant at the 1% level for the three specifications, which indicates that price volatility depends on its history: greater values of recent residuals of the mean equation produce higher present volatility.

On average, the level of maize price volatility has decreased over the last 10 years. Results also suggest that price volatility is not the same all year through. Prices are significantly more volatile during the harvest season (we did not find any significant effect of the lean season dummy on price volatility), as was also observed in other recent empirical works (Jordaan *et al.*, 2007, Kilima *et al.*, 2008, Maître d'Hôtel *et al.*, 2013). It may be related to the fact that supply and demand moves may be more unpredictable in harvest season, for example because of oligopolistic storage strategies and of food aid programs' operations.

We find that maize international prices have a small negative effect on rural markets price volatility. A possible interpretation is that when international maize prices are high, Burkina Faso stops importing grain, thus protecting its domestic markets from a volatility imported from international markets. We have said already that these imports are quite small, but they may be sufficient to create some unexpected price shifts in some markets.

Prices are more volatile in remote markets, this effect being robust to the three proxies used for transport costs and to the inclusion of climatic and ethnic control variables (Table 1). This confirms our main proposition in this article. The coefficient is greater in the market-specific dynamic estimation than in the common dynamic estimation. In the common dynamic estimation (Table 1), the coefficient varies from 0.09 in specification [4] to 0.38 in specification [7]. A coefficient of 0.38 means that one more minute of transport between the rural market and Ouagadougou (the average being 207 min) increases volatility by 0.38, the average being 235. In relative terms, this means that a 1% increase in transport time produces a 0.4% increase in volatility, on average. In the market-specific

estimation, where volatility is probably better extracted from regular price dynamics, the coefficient varies from 0.41 to 1.02, meaning that one more minute of transport increases volatility by 0.41–1.02 (the average being 294). In relative terms, this means that 1% increase in transport cost produces a 0.35–0.86% increase in volatility.

Surprisingly enough, travel time to the border has no stable effect on price volatility. This may be due to the fact that exchanges with border countries may have had stabilizing effects some years and destabilizing effects some other years. Even though exchanges in general should have a stabilizing effect, it can occur that foreign countries export at exceptionally low prices or import at exceptionally high prices, which may foster domestic prices drops or spikes.

Markets located in North Sahelian zone, characterised by a very dry climate, present significantly lower maize price volatility than markets in Southern areas that are more favourable to maize growing (South Sahelian, North Soudanian and South Soudanian zones) and where maize production may exceed maize consumption. This result is consistent with Kilima *et al.* (2008) who find that price volatility tends to be higher in maize-surplus markets than in maize-deficit markets. The explanation may be that demand shocks are not as frequent or as great as supply shocks.

5.3 Robustness tests

To assess the robustness of our empirical results to alternative definition of transport costs and to alternative models, we run additional estimations. Our main result on the positive effect of transport costs on maize price volatility stands for all these additional specifications. First, we proxy transport costs not solely as the time travel to Ouagadougou but as the time travel, for each market, to the closest urban centre, Ouagadougou and two additional cities being included in our analysis (Table 3). Second, we proxy transport costs as the sum, for each market, of its time travel to all other twenty-seven markets (Table 4). Third, we use nominal prices to test whether inflation on prices may affect our main result (Table 5).

5.3.1 Time to the closest city

If we proxy remoteness by the travel time between each market and its closest city and not only to the capital city, the positive effect of remoteness on volatility holds (Table 3).

5.3.2 Cumulative time travel to other markets

If we consider trade as a network and thus define remoteness as the distance of one market to all the other markets, computing for each market a cumulative time travel to the other twenty-seven markets, the positive effect of remoteness on volatility holds (Table 4).

5.3.3 Nominal maize prices

We run the same ARCH models on series of nominal prices instead of deflated ones. Table 5 reports the estimation result when prices are expressed in nominal prices. Results are very similar and the positive and significant impact of travel time on maize price volatility holds.

Table 3: Effect of Transport Costs on Maize Price Volatility, Costs being Proxied by the Distance to the Closest City

	[12]		[13]		[14]		[15]	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	29.97***	208.81***	40.27***	209.92***	33.33***	−151.46***	31.19***	57.57
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.123)
Arch Term		0.20***		0.23***		0.14***		0.15***
		(0.000)		(0.000)		(0.000)		(0.000)
Lagged price	0.85***	0.39***	0.85***	0.31***	0.93***	1.04***	0.91***	1.41***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
International price	0.06***	−0.31***	0.06***	−0.24***	0.04***	−0.54***	0.04***	−0.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exchange rate	−0.03***	−0.03	−0.04***	−0.03	−0.04***	0.23***	−0.03***	0.01
	(0.000)	(0.669)	(0.000)	(0.564)	(0.000)	(0.004)	(0.000)	(0.927)
Harvest dummy	−6.22***	91.52***	−6.42***	92.41***	−6.16***	134.39***	−6.07***	115.90***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	1.61***	−3.99*	1.41***	−2.31**	1.27***	−1.52	1.07***	0.03
	(0.000)	(0.061)	(0.000)	(0.036)	(0.000)	(0.625)	(0.002)	(0.987)
Time to border	0.06***	−0.02	0.06***	−0.02	0	0.13***	0	−0.39***
	(0.000)	(0.807)	(0.000)	(0.846)	(0.719)	(0.000)	(0.328)	(0.000)
Time to closest city	−0.04***	0.21***	−0.02***	0.19**	−0.01*	0.23***	−0.01	0.44***
	(0.000)	(0.000)	(0.004)	(0.013)	(0.095)	(0.000)	(0.336)	(0.000)
Trend	−0.06***	−1.59***	−0.05***	−1.56***	−0.05***	−1.02***	−0.06***	−1.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	YES	YES	YES	NO	NO	NO	NO
Annual rainfall			−0.009***	−0.01				
			(0.001)	(0.790)				
South Sahelian climate					−1.23	39.68***		
					(0.176)	(0.000)		
North Soudanian climate					−3.28***	97.24***		
					(0.000)	(0.000)		

South soudanian climate			−4.24***	110.58***	
			(0.000)	(0.000)	
Peulh ethny					3.11***	−56.48***
					(0.004)	(0.000)
Gourmatche ethny					0.33	11.09
					(0.823)	(0.469)
Bissa ethny					−0.46	−62.32***
					(0.713)	(0.000)
Lobi ethny					1.53	−27.89**
					(0.282)	(0.042)
Senoufo ethny					−3.07**	−1.93
					(0.016)	(0.855)
Dagara ethny					−2.17**	−32.35***
					(0.021)	(0.000)
Bobo ethny					−2.95***	60.21***
					(0.003)	(0.000)
Gourounsi ethny					−0.8	0.18
					(0.441)	(0.982)
Mossi ethny					0.61	−9.21
					(0.512)	(0.255)
N	3472	3472	3472	3472	
R squared	0.8371	0.837	0.831	0.8325	

p-values in brackets.
*Significant at 10%; **significant at 5%; ***significant at 1%.
[12] Market dummies.
[13] Rainfall and market dummies.
[14] Climatic zone dummies.
[15] Ethnic group dummies.

Table 4: Effect of Transport Costs on Maize Price Volatility, Costs Being Proxied by the Cumulative Distance to All Markets

	[16]		[17]		[18]		[19]	
	Mean equation	Variance equation	Mean equation	Variance equation	Mean equation	Variance equation	Mean equation	Variance equation
Constant	48.86***	207.87***	50.46***	208.54***	34.46***	−65.65***	34.50***	69.67*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.054)
Arch term		0.20***		0.21***		0.17***		0.16***
		(0.000)		(0.000)		(0.000)		(0.000)
Lagged price	0.84***	0.75***	0.84***	0.74***	0.92***	1.45***	0.90***	1.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
International price	0.05***	−0.42***	0.05***	−0.42***	0.04***	−0.49***	0.04***	−0.58***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exchange rate	−0.04***	−0.18*	−0.04***	−0.18*	−0.03***	−0.07***	−0.03***	−0.20***
	(0.000)	(0.080)	(0.000)	(0.082)	(0.000)	(0.006)	(0.000)	(0.002)
Harvest dummy	−6.20***	47.75***	−6.17***	44.09***	−5.97***	117.86***	−6.15***	110.28***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	1.41***	−8.17**	1.40***	−8.22**	1.02***	0.85	1.06***	1.71
	(0.000)	(0.011)	(0.001)	(0.011)	(0.009)	(0.500)	(0.009)	(0.428)
Time to the border	0.02***	−0.07	0.03***	−0.09	0.00	−0.10***	0.01	−0.37**
	(0.000)	(0.128)	(0.000)	(0.168)	(0.516)	(0.000)	(0.348)	(0.000)
Cumulative time	−0.00***	0.01***	−0.00***	0.01***	0.00**	0.01***	0.00*	0.02***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.010)	(0.000)	(0.094)	(0.000)
Trend	−0.05***	−1.67***	−0.05***	−1.66***	−0.05***	−1.11***	−0.05***	−1.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	YES	YES	YES	NO	NO	NO	NO
Annual rainfall			−0.01***	0.01				
			(0.000)	(0.818)				
South Sahelian climate					−2.57***	43.11***		
					(0.004)	(0.000)		
North Soudanian climate					−3.78***	94.39***		
					(0.000)	(0.000)		

South Soudanian climate			−4.12**	59.08***		
			(0.000)	(0.000)		
Peulh ethny					3.72***	−55.93***
					(0.001)	(0.000)
Gourmantche ethny					0.85	9.97
					(0.561)	(0.524)
Bissa ethny					−0.46	−44.39***
					(0.719)	(0.000)
Lobi ethny					1.78	−4.88
					(0.165)	(0.700)
Senoufo ethy					−1.28	−85.27***
					(0.476)	(0.000)
Dagara ethny					−2.10**	0.69
					(0.018)	(0.852)
Bobo ethny					−1.80*	7.45*
					(0.068)	(0.052)
Gourounsi ethny					−1.13	17.01**
					(0.311)	(0.017)
Mossi ethny					0.25	−2.78
					(0.766)	(0.594)
N	3472	3472	3472	3472		
R squared	0.8732	0.8373	0.8311	0.8331		

p-values in brackets.
*Significant at 10%; **significant at 5%; ***significant at 1%.
[16] Market dummies.
[17] Rainfall and market dummies.
[18] Climatic zone dummies.
[19] Ethnic group dummies.

Table 5: Effect of Transport Costs on Maize Price Volatility, Estimations led with Nominal Maize Prices

	[20]		[21]		[22]		[23]	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	34.79***	181.45***	43.05***	182.8***	35.27***	−66.11	34.22***	41.96***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.103)	(0.000)	(0.000)
Arch Term		0.20***		0.22***		0.16***		0.15***
		(0.000)		(0.000)		(0.000)		(0.000)
Nominal lagged price	0.87***	0.59***	0.85***	0.53***	0.94***	1.64***	0.92***	1.61***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nominal International price	0.09***	−0.31***	0.08***	−0.21***	0.05***	−0.53***	0.05***	−0.48***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nominal Exchange rate	−0.04***	−0.07	−0.05***	−0.06	−0.04***	0	−0.04***	−0.07**
	(0.000)	(0.324)	(0.000)	(0.392)	(0.000)	(0.986)	(0.000)	(0.017)
Harvest dummy	−6.55***	117.2***	−6.56***	97.55***	−6.05***	120.12***	−6.05***	115.05***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean dummy	2.01***	−4.06**	1.9***	−4.46***	1.54***	−1.65	1.55***	−4.2
	(0.000)	(0.047)	(0.000)	(0.003)	(0.000)	(0.588)	(0.000)	(0.123)
Time to border	0.01***	−0.03	0.04***	−0.02	0.004	−0.20***	0.003	−0.45***
	(0.006)	(0.642)	(0.000)	(0.839)	(0.181)	(0.000)	(0.523)	(0.000)
Time to Ouaga	−0.02***	0.09**	−0.03**	0.12***	−0.01**	0.28***	−0.01**	0.43***
	(0.000)	(0.045)	(0.042)	(0.007)	(0.019)	(0.000)	(0.048)	(0.000)
Trend	−0.05***	−1.29***	−0.04***	−1.4***	−0.05***	−1.10***	−0.04***	−1.15***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market dummies	YES	YES	YES	YES	NO	NO	NO	NO
Annual rainfall			−0.009**	−0.02				
			(0.012)	(0.696)				
South Sahelian climate					−1.95**	44.84***		
					(0.016)	(0.000)		
North Soudanian climate					−2.52***	78.70***		
					(0.002)	(0.000)		

South Soudanian climate			−2.17**	29.99***	
			(0.031)	(0.004)	
Peulh ethny					2.71**	−23.21***
					(0.001)	(0.006)
Gourmantche ethny					0.99	71.89***
					(0.438)	(0.000)
Bissa ethny					−0.41	−25.79**
					(0.718)	(0.015)
Lobi ethny					2.92**	−23.00*
					(0.040)	(0.065)
Senoufo ethny					−0.47	−80.1***
					(0.783)	(0.000)
Dagara ethny					−1.03	−22.22***
					(0.204)	(0.000)
Bobo ethny					−0.76	−0.12
					(0.445)	(0.983)
Gourounsi ethny					−0.74	14.35
					(0.475)	(0.103)
Mossi ethny					−0.1	25.17***
					(0.906)	(0.000)
N	3472	3472	3472	3472	
R squared	0.8601	0.8604	0.8547	0.856	

p-values in brackets.
*Significant at 10%; **significant at 5%; ***significant at 1%.
[20] Market dummies.
[21] Rainfall and market dummies.
[22] Climatic zone dummies.
[23] Ethnic group dummies.

6. Conclusion

Drawing on the case of maize in Burkina Faso, we analyze the effect of market remoteness on price volatility. We develop a model of price formation to shed light on the local causes of volatility in rural markets. The empirical estimations we led on twenty-eight markets established that markets that are close to the main cities and where road is paved display less volatile price series. Results also show that markets that are close to maize border-crossing points show more volatile prices, which indicate a low level of regional integration between Burkina Faso and border countries.

These findings suggest that policies aimed at reducing maize price volatility should be targeted towards infrastructure development and promote regional integration and economic development within the ECOWAS area. For instance, authorities could support remote markets by providing rural road infrastructures, thereby contributing to linking remote markets with major consumption centres across the country as well as in neighboring countries. Other studies came to the similar policy conclusion of the importance of rural roads on rural development (Jacoby, 2000), agricultural specialisation (Qin and Zhang, 2016) and poverty reduction (Van de Walle, 2002). Without such rural roads investments, it will be difficult to improve the commercialisation of agricultural products in remote areas and reduce price volatility across markets in Burkina Faso.

Supplementary material

Supplementary material is available at *Journal of African Economies* online.

Acknowledgements

This paper is a product of SUPAGRO and CIRAD Economic Departments. We are grateful to Luc Christiaensen, Pierre Courtois, Brian Dillon, Christopher L. Gilbert, Jonathan Kaminski, Sophie Thoyer and two anonymous referes for their suggestions and comments that have significantly improved the paper.

References

Abdulai A. (2000) 'Spatial Price Transmission and Asymmetry in the Ghanaian Maize Market', *Journal of Development Economics*, 63 (2): 327–49.

Aker J. C., Klein M. W., O'Connell S. A., Yang M. (2014) 'Borders, Ethnicity And Trade', *Journal of Development Economics*, 107 (1): 1–16. http://works.swarthmore.edu/fac-economics/70

Anderson J. E., Marcouiller D. (2002) 'Insecurity and the Pattern of Trade: An Empirical Investigation', *Review of Economics and Statistics*, 84 (2): 342–52.

Anderson J. E., Van Wincoop E. (2004) 'Trade Costs', *Journal of Economic Literature*, 42 (3): 691–751.

Badiane O., Shively G. E. (1998) 'Spatial Integration, Transport Costs, and the Response of Local Prices to Policy Changes in Ghana', *Journal of Development Economics*, 56 (2): 411–31.

Barrett C. (1996) 'On Price Risk and the Inverse Farm Size – Productivity Relationship', *Journal of Development Economics*, 51 (2): 193–215.

Barrett C. (1997) 'Liberalization and Food Price Distributions: ARCH-M Evidence from Madagascar', *Food Policy*, 22 (2): 155–73.

Beck S. E. (1993) 'A Rational Expectations Model of Time Varying Risk Premia in Commodities Futures Markets: Theory and Evidence', *International Economic Review*, 34 (1): 149–68.

Bollerslev T. (1986) 'Generalized Autoregressive Conditional Heteroskedasticity', *Journal of Econometrics*, 31 (3): 307–27.

Brenton P. (2012) 'Africa Can Help Feed Africa: Removing Barriers to Regional Trade in Food Staples,' Discussion Paper, The Worldbank, Washington, DC.

Brunt L., Cannon E. (2014) 'Measuring Integration in the English Wheat Market, 1770–1820: New Methods, New Answers', *Explorations in Economic History*, 52: 111–30.

Buys P., Deichmann U., Wheeler D. (2010) 'Road Network Upgrading and Overland Trade Expansion in Sub-Saharan Africa', *Journal of African Economies*, 19 (3): 399–432.

Cairncross F. (1999) 'The Death of Distance: How the Communication Revolution Will Change Our Lives', *American Quarterly-Minneapolis*, 51: 160.

Carrere C., Schiff M. (2005) 'On the Geography of Trade. Distance is Alive and Well', *Revue Economique*, 56: 1249–74.

Dahlman C. J. (1979) 'The Problem of Externality', *The Journal of Law & Economics*, 22 (1): 141–62.

Disdier A.-C., Head K. (2008) 'The Puzzling Persistence of the Distance Effect on Bilateral Trade', *The Review of Economics and statistics*, 90 (1): 37–48.

Driscoll J. C., Kraay A. C. (1998) 'Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data', *Review of Economics and Statistics*, 80 (4): 549–60.

Engle R. (1982) 'Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation', *Econometrica: Journal of the Econometric Society*, 50 (4): 987–1007.

Fafchamps M. (1992) 'Cash Crop Production, Food Price Volatility and Rural Market Integration in the Third World', *American Journal of Agricultural Economics*, 74 (1): 90–9.

Francois J., Manchin M. (2013) 'Institutions, Infrastructure, and Trade', *World Development*, 46: 165–75.

Gilbert C., Morgan W. (2010) 'Food Price Volatility', *Philosophical Transactions of the Royal Society*, 365: 3023–34.

Hummels D. L., Schaur G. (2010) 'Hedging Price Volatility Using Fast Transport', *Journal of International Economics*, 82 (1): 15–25.

Im K. S., Pesaran M. H., Shin Y. (2003) 'Testing for Unit Roots in Heterogeneous Panels', *Journal of Econometrics*, 115 (1): 53–74.

Jacks D. S., O'Rourke K. H., Williamson J. G. (2011) 'Commodity Price Volatility and World Market Integration Since 1700', *Review of Economics and Statistics*, 93 (3): 800–13.

Jacoby H. G. (2000) 'Access to Markets and the Benefits of Rural Roads', *Economic journal*, 713–37.

Jordaan H., Grove B., Jooste A., Alemu Z. (2007) 'Measuring the Price Volatility of Certain Field Crops in South Africa Using the ARCH/GARCH Approach', *Agrekon*, 46 (3): 306–22.

Kapetanios G., Mitchell J., Shin Y. (2014) 'A Nonlinear Panel Data Model of Cross-Sectional Dependence', *Journal of Econometrics*, 179 (2): 134–57.

Kilima F. T. M., Chung C., Kenkel P., Mbiha E. R. (2008) 'Impacts of Market Reform on Spatial Volatility of Maize Prices in Tanzania', *Journal of Agricultural Economics*, 59 (2): 257–70.

Limao N., Venables A. J. (2001) 'Infrastructure, Geographical Disadvantage, Transport Costs and Trade', *The World Bank economic review*, 15 (3): 451–79.

Maître d'Hôtel E., Le Cotty T., Jayne T. (2013) 'Trade Policy Inconsistency and Maize Price Volatility: An ARCH Approach in Kenya', *African Development Review*, 25 (4): 607–20.

Minot N. (2010) *Transmission of World Food Price Changes to Markets in Sub-Saharan Africa*. Washington, DC: International Food Policy Research Institute.

Minot N. (2014) 'Food Price Volatility in Sub-Saharan Africa: Has It Really Increased?', *Food Policy*, 45: 45–56.

Minten B., Kyle S. (1999) 'The Effect of Distance and Road Quality on Food Collection, Marketing Margins, and Traders' Wages: Evidence from the Former Zaire', *Journal of Development Economics*, 60 (2): 467–95.

Minten B., Randrianarison L. (2003): 'Ètude sur la formation des prix du rix local à Madagascar,' in *A Paper Prepared for the Conference on 'Agriculture et Pauvrete'*, Antananarivo, Madagascar.

Pesaran M. H. (2007) 'A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence', *Journal of Applied Econometrics*, 22 (2): 265–312.

Pesaran M. H., Smith L. V., Yamagata T. (2013) 'Panel Unit Root Tests in the Presence of a Multifactor Error Structure', *Journal of Econometrics*, 175 (2): 94–115.

Pomfret R., Sourdin P. (2010) 'Why Do Trade Costs Vary?', *Review of World Economics*, 146 (4): 709–30.

Prakash A. (2011) *Why Volatility Matters*. Rome: FAO, pp. 3–26.

Qin Y., Zhang X. (2016) 'The Road to Specialization in Agricultural Production: Evidence from Rural China', *World Development*, 77: 1–16.

Rapsomanikis G., Mugera H. (2011) 'Price Transmission and Volatility Spillovers in Food Markets of Developing Countries', in *Methods to Analyse Agricultural Commodity Price Volatility*. New York: Springer, pp. 165–79.

Roehner B. M. (1996) 'The Role of Transportation Costs in the Economics of Commodity Markets', *American Journal of Agricultural Economics*, 78 (2): 339–53.

Samuelson P. A. (1952) 'Spatial Price Equilibrium and Linear Programming', *The American economic review*, 283–303.

Shepherd B., Wilson J. S. (2007) 'Trade, Infrastructure, and Roadways in Europe and Central Asia: New Empirical Evidence', *Journal of Economic Integration*, 723–47.

Shively G. (1996) 'Food Price Variability and Economic Reform: An ARCH Approach for Ghana', *American Journal of Agricultural Economics*, 78: 126–36.

Stifel D., Minten B. (2008) 'Isolation and Agricultural Productivity', *Agricultural Economics*, 39 (1): 1–15.

Van de Walle D. (2002) 'Choosing Rural Road Investments to Help Reduce Poverty', *World Development*, 30 (4): 575–89.

Williamson O. E. (1979) 'Transaction-Cost Economics: The Governance of Contractual Relations', *The journal of law & economics*, 22 (2): 233–61.

Ecological Economics 176 (2020) 106716

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

How Might Climate Change Influence farmers' Demand for Index-Based Insurance?☆

A. Leblois[a,*], T. Le Cotty[b], E. Maître d'Hôtel[c]

[a] CEE-M, Univ Montpellier, CNRS, INRAE, Institut Agro, Montpellier, France
[b] CIRAD, CIRED, France
[c] CIRAD, MOISA, France

ARTICLE INFO

Keywords:
Index-Based Insurance
Extreme Events
Frequency
Basis Risk

JEL Codes:
G22
O12
Q18

ABSTRACT

The low observed uptake of non-subsidised index-based insurance policies in developing countries has been puzzling researchers for about a decade. This paper analyses the role of drought frequency in farmers' demand for index-based insurance in developing countries. While it is typically assumed that an increase in exposure to risk would result in higher demand for index insurance, this paper finds the opposite: an increase in drought frequency may result in lower demand for index insurance under fairly standard conditions. In an expected utility model, we show that the demand for insurance is an inverted U function of drought frequency. We further show that downside basis risk decreases insurance demand under frequent drought conditions. It implies that insurance against similar but more frequent events cannot meet large demand from farmers. To check the empirical relevance of these effects, we conduct an insurance field experiment in Burkina Faso with 205 farmers. We analyse insurance demand for different drought frequencies, different levels of basis risks and different loading factors through incentivised lottery choices. This analysis confirms that for higher drought frequencies, insurance demand is lower. Insurance demand also decreases with basis risk and the loading factor.

1. Introduction

In developing countries, index-based insurance schemes are becoming more widespread. Yet, despite growing interest among donors, insurers and banks, there is a low take-up rate of index-based insurance products among farmers (Cole et al., 2013; Giné and Yang, 2009). Substantial progress has been made in the economic literature in understanding the factors that may prevent farmers from purchasing index-based insurance in developing countries, such as cost and access to reliable information, and these factors are not easy to overcome (Platteau et al., 2017). But the nature of the risk itself may affect demand for insurance. And in this respect, the effect of drought frequency - and more generally damage frequency - on insurance take-up has not received much attention, apart from the literature on low probability risk problems (Slovic et al., 1977; Tversky and Kahneman, 1992; Kunreuther and Pauly, 2004).

Few climatologists have certainties about how climate change might influence precipitations in the Sahel, but one likely scenario is that drought may be more frequent. As mentioned by Panthou et al. (2018), there seem to be a recent recovery in annual cumulative rainfall, but this recovery is associated with an increase of rainfall intensity and a lower number of rainy days during the rainfall season, thus creating more frequent dry spells.

In this paper we look at the role of drought frequency on demand for index-based insurance in Burkina Faso. Rainfall season quality is critical for agriculture, and climate change may alter the frequency, severity, duration and timing of drought and the impact of such a change on demand for insurance is not known. We only consider here one dimension of climate change, namely the increase in drought frequency while we take severity, duration and timing as given. Several reactions of the insurer to this evolution could be considered, notably premium increase, or partial indemnification. We focus on the premium increase, for clarity, and because our focus is on the demand side of insurance[1]. However, we do not know a priori whether such change will favour or

☆ This paper is produced by the INRAE and CIRAD Economic Departments. It has benefited from funding from the European Union under the FARMAF project, grant n° 2011/260-875)

* Corresponding author.
E-mail address: antoine.leblois@inrae.fr (A. Leblois).

[1] If climate change increases the probability of occurrence of a shock, we expect the insurer to adjust insurance products to the raise of frequency by modifying the strike level (i.e. the threshold of the weather index) and/or by increasing insurance premiums and indemnifications).

https://doi.org/10.1016/j.ecolecon.2020.106716
Received 23 April 2019; Received in revised form 19 March 2020; Accepted 16 May 2020
Available online 03 June 2020
0921-8009/

discourage insurance subscription, because both the price of insurance and the protection provided are greater.

Many factors contributing to the low demand for insurance in developing countries have been addressed in the economic literature.

A first set of factors is related to the demand side of index-based insurance products. Farmers may be liquidity constrained, especially in the absence of credit markets, and thus unable to afford insurance premiums (Cole et al., 2013; Carter et al., 2016). They also often experience a seasonality in their credit constraint (Dercon and Krishnan, 2000), the premium being generally paid before sowing, which corresponds to the end of the lean season when the credit constraint is particularly tied. Casaburi and Willis (2018) showed that interlinked insurance contracts deducting premiums from farmers revenues at harvest time significantly increase take-up rates. However, uncertainty in the payout also matters, Casaburi and Macchiavello (2019) show evidence that farmers are willing to incur sizable costs to receive infrequent payments as a commitment saving device. Alternatively, farmers may find index-based insurance too complex to understand (Gaurav et al., 2011), for instance because of low financial literacy (Cai et al., 2015). They may not trust the insurance supplier to provide the promised payouts Patt et al., 2010; Cai et al., 2009; Dercon et al., 2015). They may also already be insured through informal networks, through non-agricultural activities or through limited-liability credit contracts, which in turn limit their demand for a formal insurance product (Mobarak and Rosenzweig, 2013).

A second set of factors is related to the supply side and to the limitations of index-based insurance products, which may be too expensive or present technical deficiencies. Although satellite data may be used to overcome ground data limitations, it may be subject to biases and trust issues. The lack of quality historical data and infrastructures, such as dense networks of weather stations, remain significant obstacles to index insurance supply in many countries. Recent experiments carried out with different levels of subsidy argue in favour of a high elasticity of index-based insurance demand to insurance price (Mobarak and Rosenzweig, 2013; Karlan et al., 2014). Contract non-performance is another potential source of insurance product rejection (Doherty and Schlesinger, 1990). It is particularly relevant for index-based insurance contracts because of the imperfect correlation between the index and farmers yields. This discrepancy between insurance payouts and agricultural output, known as basis risk, may deter farmers from taking out index-based insurance (Giné et al., 2008; Giné and Yang, 2009; Cole et al., 2013; Tadesse et al., 2015; Dercon et al., 2014; Clarke, 2016). Basis risk can arise from different reasons (Leblois et al., 2014; Norton et al., 2013; Dalhaus et al., 2018) and frequenctly turns out to be a downside basis risk, that is a yield shock situation with no payout triggered by the index[2]. If this happens, the farmer finds herself in a worse situation with insurance after paying a premium than without insurance (Clarke, 2016).

A third set of factors may be due to the nature of climate risk itself. The probability of risk occurrence could be a potential obstacle to insurance subscription and to our knowledge, it has not been addressed in the specific literature on index insurance.

The literature on optimal insurance addresses the question of the property of risk on the optimal contract from the insurer's point of view, under the constraint that farmers subscribe (Chambers, 1989; Mahul, 2001). The farmers' demand is studied through the lens of the participation constraint. In their framework, a farmer participates to the insurance scheme if and only if her expected utility with insurance is greater than her expected utility without insurance. The sign of expected gains from insurance suffices to design optimal insurance contract, but if we want to address the demand side of existing index insurances, it is crucial to study also the size of expected gains.

Theoretical and empirical evidence about the potential impact of shock frequency on insurance demand have focused on low-probability events. Literature on disaster coverage in particular highlights low take-up for low-probability risks (Slovic et al., 1977). Behaviour in relation to probability-based insurance is used in Kahneman and Tversky (1979)'s seminal paper to explain the limited demand for insurance against low-probability risks (typically disaster insurances). Kunreuther and Slovic (1978); Hertwig et al. (2004); Kunreuther et al. (2001) argue that low probabilities are more difficult to perceive than high probabilities. Raschky et al. (2013); Kousky and Cooke (2012); Grislain-Letrémy (2016) find empirical support for this hypothesis in various countries. However, some experimental results provide empirical evidence suggesting the inverse relationship and highlight the fact that insurance demand for low-probability risks may be higher than that for higher-probability risks. McClelland et al. (1993) and Laury et al. (2009) have conducted two experiments showing that demand for insurance decreases when the probability of the shock increases[3]. In most cases, authors simultaneously test an increase in shock probability, and a decrease in the damage magnitude to keep the premium constant (Slovic et al., 1977) or small enough (Laury et al., 2009). This implies that they compare different types of damage, not different frequencies of a same damage.

Furthermore, this literature has not really looked the effect of shock frequency for a broad range of probability events. The only paper we found that investigates the impact of shock frequency on insurance demand in the case of high-probability events is Norton et al. (2014). The authors demonstrate, using a choice experiment based on similar commercial insurance contracts sold locally, that insurance take up is much higher among Ethiopian farmers in the case of high frequency risks. Their main result is that insurance demand increases with the frequency of insured events, but again, in a setting where the frequent damage is not more expensive than the infrequent damage.

To measure the specific effect of frequency change and not the combined effect of a frequency change and a magnitude change, we propose an experiment and a theoretical model where the damage magnitude is constant as its frequency increases. The corollary is that the premium increases, as it would typically do when climate change occurs. Given that farmers already face zero-yield situations in the Sahel, and that climate change may increase the occurrence of such events, it seems relatively reasonable to bound damage magnitude.

We build an expected utility (EU) discrete choice model of insurance derived from Doherty and Schlesinger (1990)'s conceptual model to analyse the effect of shock frequency on insurance demand for the same damage. We establish that (1) the demand for insurance is an inverted U function of shock frequency indicating that there is an optimal frequency for farmers to take out insurance, (2) for high-frequency shocks, gains from insurance become negative (3) and both optimal frequency and maximal insurable frequency decrease with basis risk and loading factor levels.

To assess the empirical relevance of these effects, we conducted an insurance field experiment with 205 farmers in Burkina Faso. Farmers were asked to choose between insurance and no insurance, in 18 lottery choices representing insurance policies with different loading factors, different levels of basis risk and different drought frequencies. Three shock frequencies were used: 1/20 (low-probability shocks that occur on average once over a 20-year period), 2/20 (intermediate-probability shocks) and 7/20 (high-probability shocks). Three levels of downside basis risk were tested for each frequency: zero (no discrepancy between the index and the yield), 1/5 and 2/5, corresponding to the probability of not getting a payout conditional upon the occurrence of a shock. Finally, two loading factors were tested for each of the above combinations: the actuarially fair rate and a loading factor of 1.5. We find that

[2] Risk of "missed crisis", as opposed to a "false alarm", corresponding to an indemnification in absence of a weather shock, see section 2.

[3] See also the literature review by Jaspersen (2015) on experimental evidence for insurance demand, for a discussion on the methods used.

an increase in basis risk or loading factor leads to lower demand for insurance, and, more originally, that an increase in drought frequency significantly reduces demand for insurance if the frequency is greater than 1/10. These experimental results are robust to different statistical specifications and consistent with the theoretical model, for frequencies beyond the optimal level.

The paper is organized as follows. In section 2 we build upon a conceptual model to account for the effect of shock frequency on insurance demand. In section 3, we present the field experiment that we conducted in Burkina Faso, and in section 4, we describe our empirical results.

2. An Index-Based Insurance Probability Model

We adapt the formal framework proposed by Doherty and Schlesinger (1990) to the binary decision to get full insurance or no insurance in the context of basis risk. In theory two types of basis risk are possible: the "false alarm", i.e. the probability of a farmer receiving an indemnification while her production has not been impacted, and the "missed crisis" (or downside basis risk), i.e. the probability of a farmer receiving no indemnification while her production has been impacted by a random shock that is theoretically included in the contract. We focus here on downside basis risk because from the farmer's point of view, only the downside basis risk is an actual risk, whereas the "false alarm" is a risk for the insurer, which is not our perspective here. In the case of a continuous risk, a similar asymmetry exists and the downside risk is then typically defined by the semi-variance of profits (Turvey and Nayak, 2003; Conradt et al., 2015).

Downside basis risk can be formalized as a non performing contract (Doherty and Schlesinger, 1990), be it an imperfection in the insurance scheme or a default by the insurer. We note p the frequency of drought and r the downside basis risk, i.e. the probability of a farmer who has contracted an insurance receiving no indemnity conditional on the occurrence of the shock. It encompasses both imperfections in the index and insurer's failings. The probability of a farmer who has contracted an insurance suffering a shock without receiving any indemnity is thus rp.

In our model, a drought is an event of prolonged low rainfall leading to shortages in water availability, such as low cumulative rainfall or unusually long or frequent dry spells that are known to have a substantial impact on agriculture when they take place during the cropping season. This impact is summarised into the crop yield decrease relatively to a normal year, and in our simplified framework, it takes a unique value L, the loss in case of a shock. If y is the farmer's income in a normal year, $y - L$ is the income in the case of a drought year. In the case of a drought, the insurer pays an indemnity L with probability $1 - r$. Let P denote the yearly premium, and $m \geq 1$ the loading factor applied by the insurer. The premium is then the average loss pL multiplied by the probability of indemnification $1 - r$ multiplied by the loading factor, $P = mp(1 - r)L$. The insurance framework probability model is summarised in Table 1. Note that an increase in downside basis risk implies a lower rate of indemnification, thus a lower premium.

The farmer's expected utility gain from taking out insurance is the difference between her expected utility with insurance and her expected utility without insurance. This supposes that the decision to take out insurance is binary, which is a simplification with regard to Doherty and Schlesinger (1990) where the decision is about choosing an insurance rate between 0 and 1. This simplification is consistent with our field experimental framework.

Table 1
Insurance framework probability model.

	Payout (1-r)	No payout (r)
No yield shock (1-p)	0	$1 - p$
Yield shock (p)	$(1 - r)p$	rp

$$\Delta EU = (1 - p)u(y - P) + (1 - r)pu(y - P) + rpu(y - P - L) - [(1 - p)u(y) + pu(y - L)] \quad (1)$$

In this expression, the first term is the expected utility in the case of no drought if the farmer has contracted an insurance, resulting from the benefit of the harvest minus the cost of the premium (ie the probability of no drought times the utility with no drought). In case of drought, there are two sub-cases. Either the farmer gets reimbursed and her utility remains the same as in the case without drought, $pu(y - P)$, or the farmer does not get reimbursed and her utility is lower, $u(y - P - L)$. The expected utility in case of drought is a combination of these two sub-cases: probability of a drought that is indemnified times utility in this case (second term), and the probability of a drought that is not indemnified times utility in this case (third term).

The fourth term is the expected utility for a farmer who does not take up the insurance and there is no drought, and the fifth term is the expected utility for a farmer who does not take up the insurance and there is a drought.

The farmer is supposed to take the insurance if she expects a higher utility, in average, if she is insured than if she is not. Thus the demand for insurance is a binary decision that depends on the sign of ΔEU. However, this decision is generally subject to individual idiosyncrasies, leading to individual heterogeneity in take-up decisions for a given set of parameters (m, p, L, y). People do not all take the same choice, even if their farming activity is the same and face the same potential insurance contract. To account for these idiosyncrasies we define individual demand $x_i(p, y, L, m)$ as follows:

$$x_i(p, y, L, m) = \begin{cases} 0 & if \quad \Delta EU + \varepsilon_i \leq 0 \\ 1 & if \quad \Delta EU + \varepsilon_i > 0 \end{cases} \quad (2)$$

so that the probability that a farmer gets the insurance, $E(x_i | m, p, L, y)$, equals the probability that her expected gains of insurance plus the error term is strictly positive, $prob(\Delta EU + \varepsilon_i > 0 | m, p, L, y)$, where ε_i is the error term representing idiosyncrasies. Individual demands are added together to form a collective demand $n(m, p, L, y) = \sum_{i \in [1,N]} x_i(m, p, L, y)$ where N is the total number of farmers potentially concerned by the insurance contract.

2.1. Optimal Shock Frequency in the Absence of Basis Risk

This subsection aims to provide understanding of the impact that drought frequency would have on expected gains from insurance in the absence of basis risk. To achieve this, we introduce $r = 0$ and thus $P = pmL$ into (1) and derive the two propositions:

Proposition 1. *If the insurer's profit rate is beyond a certain threshold, expected gains from insurance are negative for all drought frequencies.*

Proposition 2. *If the insurer's profit rate is below a certain threshold, in the absence of basis risk, expected gains from insurance describe an inverted u-shaped curve as drought frequency increases.*

Formal writings and proofs of all propositions are developed in the Appendix, section 6.2. As a consequence, there is a unique drought frequency (lower than 1) for which the gain from insurance is maximum.

Fig. 1 provides some intuition of proposition 2. An increase in drought frequency impacts insured and uninsured farmers in a different way. For uninsured farmers the expected utility decreases linearly as p increases, ie their marginal utility decrease is constant, $u(y) - u(y - L)$. For insured farmers utility decreases at an increasing rate, $mLu'(y - mpL)$, when p increases.

At low drought frequencies, the marginal cost of an increase in p is smaller for insured farmers than for uninsured farmers, but increasing for insured farmers and constant for uninsured farmers. As p increases

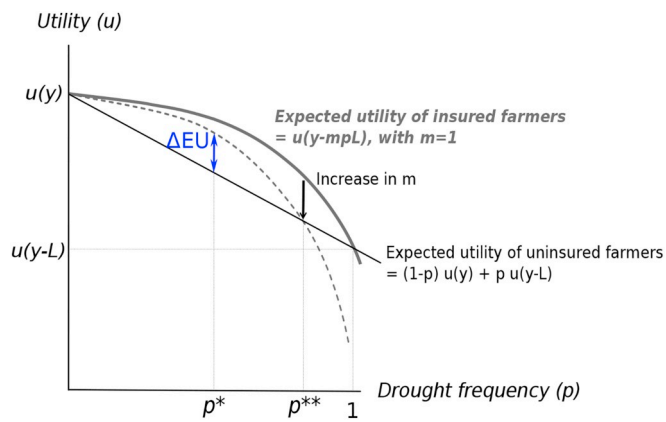


Fig. 1. Expected gain from insurance (Δ EU), without basis risk. p^* is the drought frequency that maximises the expected gain from insurance and p^*∗ is the drought frequency for which the expected gain from insurance is nil.

until p^*, it becomes more and more interesting to take out the insurance. At p^*, the marginal cost of an increase in p for insured farmers is equal to the marginal cost of an increase in p for uninsured farmers. At this point the benefit of being insured is maximal. And for higher values of p, the marginal cost of an increase in p is greater for insured farmers. The expected utility of insured farmers decreases faster than the utility of uninsured farmers as p increases. It is still profitable to be insured, but the gain from being insured decreases as p increases. As p approaches 1, the utility for insured farmers $u(y - mpL)$ becomes close to the utility for uninsured farmers $pu(y - L) + (1 - p)u(y)$, all the more as m is also close to one.

The case where p approaches 1 is implausible in practice, which tends to reduce the range of observable probabilities where ΔEU decreases with p. For instance if $p^* = 0.5$, it is unlikely that the decreasing side of the u-shaped curve can be empirically observed because farmers would stop considering drought as a risk if it occurs more often than every two years. This case of hyper-frequent droughts is useful only from theoretical point of view, to understand why farmers stop getting insurance before this upper limit. If $p^* = 0.1$, it is more likely that the decreasing side of the u-shaped curve can be validated empirically.

2.2. Optimal Shock Frequency with Basis Risk

This subsection aims to show that downside basis risk does not qualitatively alter the main result of the previous subsection.

Proposition 3.. *If the insurer's profit rate is not too high, in case of downside basis risk, the gain from insurance is an inverted u-shape curve as drought frequency increases. For common utility functions, downside basis risk has a negative impact on insurance take up.*

Proof is given in the Appendix, section 6.2.

The incentive to take out insurance first increases and then decreases with p. In other words, if shocks are too rare, gains from insurance are low and if shocks are too frequent, gains are low as well. Below we provide some intuition of this result. The principle is as above, except that the benefit of insurance is risky. Starting from a virtual situation where drought is very rare, the premium is cheap, but the indemnity is rare, so that the gain from insurance is low.

Fig. 2 represents farmers' utility after the cropping season. Again, this utility is independent of p for unisured farmers, and decreasing with p for insured farmers, because the premium increases with p. Insured farmers in case of a non indemnified drought get the worse pay off, all the more as p increases. The corresponding expected utilities are drawn on Fig. 3 in the case where the expected utility of insured farmers in the case of a non indemnified drought, $rpu(y - mp(1 - r)L - L)$, increases with p and is concave on $[0,1]$, while the expected

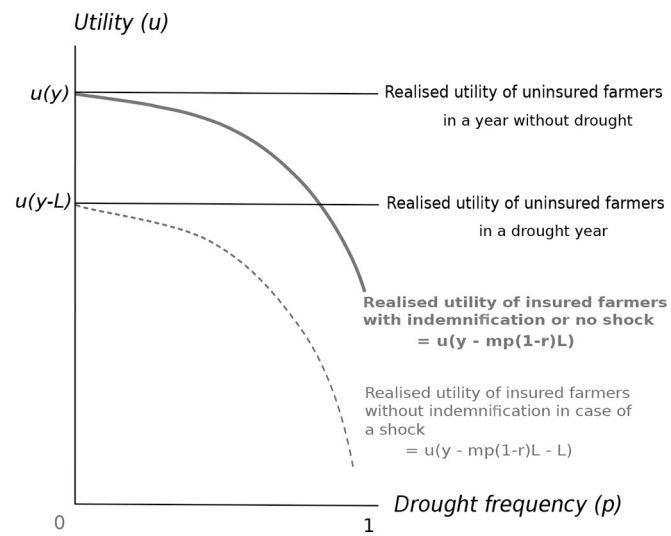


Fig. 2. Realised utility of insured and uninsured farmers.

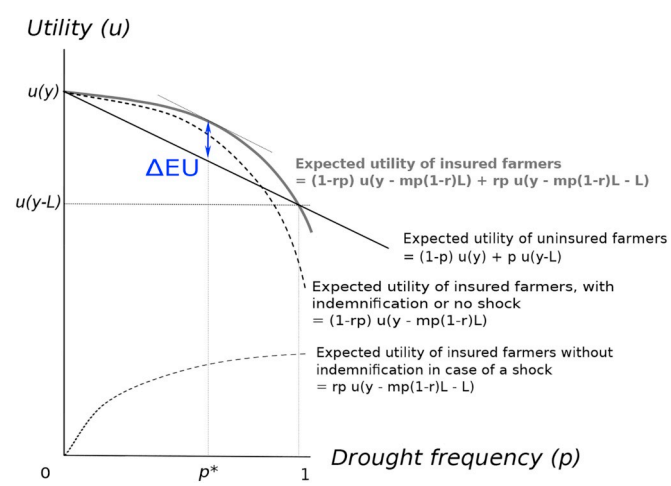


Fig. 3. Gain from insurance: expected utility of uninsured and insured farmers, in the case where $L \in \left[\frac{2ry}{m(1-r)(2rp+\rho(1-rp))}; \frac{y}{mp(2-\rho)(1-r)+1}\right]$. p^* is the drought frequency that maximises the expected gain from insurance.

utility of insured farmers in the case of indemnification, $(1 - rp)u(y - mp(1 - r)L)$ decreases with p and is concave on $[0,1]$. This is the case for instance with a CRRA utility function of parameter ρ if $L \in \left[\frac{2ry}{m(1-r)(2rp+\rho(1-rp))}; \frac{y}{mp(2-\rho)(1-r)+1}\right]$. Note that these restrictions are imposed for illustration in Fig. 3 but they are not necessary for proposition 3. The expected utility of insured farmers (plein curve at the top) is the sum of the expected utility of insured farmers in case of a non indemnified drought (upward sloping dashed curve) and the expected utility of insured farmers in case of an indemnified drought (downward sloping dashed curve).

2.3. Expected Impacts of Drought Frequency on Insurance Demand

If the loading factor is not too high, the expected impact of an increase in drought frequency is a decrease in the demand for insurance, provided drought frequency has reached a threshold value strictly inferior to 1. Furthermore, the demand for insurance is expected to decrease when the loading factor increases, and with some additional restrictions, the demand for insurance is expected to decrease when downside basis risk increases. See proofs in the appendix, section 6.2.

If the loading factor is not too high, basis risk tends to decrease subscription. This implies that the maximal insurable shock frequency

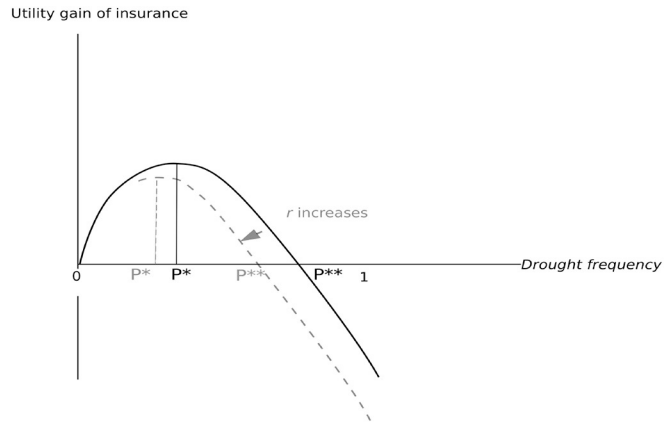


Fig. 4. Expected effect of an increase in basis risk (r) on demand for index-based insurance.

decreases as basis risk increases. Fig. 4 shows the expected effect of an increase in basis risk on expected utility.

3. Experimental Design

In November 2015, we conducted a field experiment with 205 farmers in Burkina Faso to look at the influence of different drought insurance policies on farmers' insurance demand. The insurance policies varied in terms of shock frequency, basis risk and loading factor. Our experiment took place in the field which improves external validity of experimental results, and has been raised by Gneezy and Imas (2017) as a tool "to complement traditional Randomized Control Trials in collecting covariates to test theoretical predictions and explore behavioral mechanism" at limited costs.

Agriculture in Burkina Faso is dominated by grain and cotton production. Grain production tends to be oriented towards self-sufficiency strategies, especially for millet and sorghum. Maize is partly sold on domestic markets. Millet, sorghum and maize are rain-fed crops: grain yields are highly dependent on the occurrence of drought. Our experiment took place after the end of the rainy season, which ends in Octobre in Burkina Faso, where the dry season then runs until April.

3.1. Sample Description

Nine villages were randomly selected in two different administrative units (*départements*) of Burkina Faso: Yako and Komsilga (see Fig. 5 in Appendix, section 6.1 for their location). An exhaustive list of villages in each unit, among which were randomly selected 4 and 5 villages, in Yako and Komsilga respectively, was provided by the *Confédération Paysanne du Faso*, the main national producers organisation, regrouping over 36 thousands of cooperatives and producer groups across the country. We conducted field experiment sessions in each village, with 20 or 25 farmers. A total of 205 producers were surveyed in the 9 villages and participated in the insurance field experiment. The participants were arbitrarily selected by the village chief, who we asked for a representative sample of the village in terms of age, gender, income and ethnic group, provided that each participant was available for the entire half day, and was able to write a cross in the appropriate row and column identified by a figure. Nevertheless, we have no proof that our sample is representative of the villages, and there is certainly some selection bias. Our selection method was the only one we could find in order to avoid selecting too many people who were not able to respond or were not available, as random selection would have done. The survey aimed to characterise the respondents, their households and their agricultural activities. Table 2 presents the descriptive statistics of our sample.

Table 2
Household characteristics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Sex (female = 1)	205	0.3	0.5	0	1
Age	204	40	12	17	72
Ability to read	204	0.5	0.5	0	1
Number of household members	204	9	5	1	30
Total acreage (ha)	198	3.2	2.3	0.25	15
Sorghum acreage (ha)	205	1.6	1.3	0	10
Maize acreage (ha)	205	0.5	0.8	0	5
Millet acreage (ha)	205	0.7	0.8	0	4
Number of cattle	202	1	3.3	0	40

3.2. The Insurance Field Experiment

We held two main sessions to carry out the field experiment. As an introduction, we described drought index-based insurance to the farmers: its principles, the frequency of the insured droughts, the existence of basis risk, the premiums farmers would have to pay if they wanted to take out an insurance policy and the payouts they would receive from the insurer if a drought occurred and the indemnity was effectively being paid.

Then, before the first session, we carried out hypothetical training using contextualized games involving insurance contracts where farmers had to choose to take out the insurance or not, on the basis of 18 examples of insurance contracts. In this training period, no money changed hands. Then we ran incentivised versions of the same contextualized games where farmers were presented with 18 insurance contracts. Two of the 18 games, randomly selected, resulted in payments being made to the farmers (one of each session).

Insurance contracts were calibrated on existing drought index-based insurance contracts in Burkina Faso. The assumptions were: a fixed surface of 0.5 ha of maize, and a revenue of 80,000 cfa Francs (cfaF) based on maize production of 800 kg in a normal year, and extreme damage of zero production in a dry year. For each of the 18 examples, the farmers were presented with a contract defined by the probability of drought, the basis risk, the premium, and the payout. The insurance premium differed for each of the 18 products, with a minimum of 2000 cfaF (rare drought, high basis risk, no loading factor) and a maximum of 56,000 cfaF (frequent drought, no basis risk and high loading factor). Table 7 in Appendix 6.3 summarises these 18 insurance products. Insurance premiums increased mechanically with the loading factor, the frequency of the insured drought and decreased with basis risk. For each of the 18 insurance products, the farmers had to choose whether or not they wanted to take out the insurance. After the first session of nine such games without loading factor, a blindfolded child was asked to pick a ball at random in the weather lottery. If he or she picked a white ball, meaning no drought, real payouts for the first session were announced. If the child picked an orange ball, meaning drought, he/she ran a second lottery (basis risk) to determine whether or not the insurer would actually pay the indemnity. Real payouts were announced and games 10 to 18 were then similarly played (with loading factor), giving rise to another real payout.

3.3. Weather lottery

The occurrence of drought was determined by the result of a lottery, materialised by a transparent bowl with white and orange table tennis balls. The proportion of balls of each colour reflected the drought frequency. There was a total of 20 balls in the bowl, and the drought frequency varied from 1/20 to 7/20: the number of orange drought-balls varied from 1 to 7 and the number of white rain-balls varied from 13 to 19.

3.4. Basis risk lottery

The second lottery represented basis risk, and was played for contracts with basis risk (12 of the 18 games), i.e. only if a drought occurred in the first lottery. This second lottery was materialised by a transparent bucket with black and red table tennis balls. The proportion of black balls reflected the basis risk. There was a total of 5 balls and the basis risk varied from 0 to 2/5. When there was no basis risk, the basis risk lottery was not played. In the remaining cases, the number of black balls indicating risk varied from 1 to 2, while the number of red balls indicating absence of risk varied from 3 to 4.

3.4.1. Training Sessions

The training sessions involved 18 examples calibrated on the actual harvest. The first nine examples corresponded to insurance contracts with an actuarially fair rate (m = 1), while the next nine corresponded to contracts with a loading factor (m = 1.5). For each subset of nine examples, those with no basis risk were played first, and corresponded to examples 1 to 3 and 10 to 12. Examples with basis risk corresponded to examples 4 to 9 and 13 to 18.

3.4.2. Incentivised Sessions

The incentivised sessions were the same as the training sessions, except that the farmers are told that 2 of their 18 games would lead to a payment, and that this payment would be 1% of the above-mentioned amounts calibrated on the actual harvest. They had to decide whether they wanted to take out an insurance policy for 18 situations corresponding to the ones presented during the training sessions (revenue divided by 100), and 2 games were randomly selected after game 9 and 18 respectively. Payments were made at the end of the incentivised sessions. The average gains were around 700 cfaF for the first set of nine games and around 600 cfaF for the second set of nine games. The overall average gain was thus 1300 cfaF (about 2.2 USD), corresponding to about 1 to 2 working days' wages in Burkina Faso.

Because of the existence of basis risks, some farmers could lose money. This situation could occur if the following four conditions were met: the randomly paid games corresponded to one with basis risk, i.e. 4 to 9 or 14 to 18; the farmer decided to take out insurance; a drought ball is picked in the first lottery; and a black ball is picked in the basis risk lottery. We attributed a fixed loan of 840 cfaF to each participant before beginning, so that liquidity was not a constraint on participation and no farmer could lose money during the experiment. For practical reasons, no cash was manipulated during the experiment, the payment was made at the end of the experiment. Table 3 details payments for the incentivised sessions, to be multiplied by 100 to obtain contextualized revenues (see Table 7). Table 4 describes the samples for both insurance sessions.

The sequence could imply a potential effects of learning on insurance adoption (Vasilaky et al., 2019): because lottery games were not randomized, it is possible that, by increasing their understanding of the task, farmers may have improved their choices as they played one game after another, which would interfere with exogenous changes in parameters. Since the games with a loading factor were always played after the games without a loading factor, we cannot exclude the possibility that the effect attributed to the loading factor *vis à vis* take-up actually reflects the fact that farmers play better in the second session. Although we cannot rule out the possibility of a remaining learning effect in our experiment, we played multiple hypothetical training sessions before the incentivised sessions to limit such an effect. Plus, we use session and game fixed effects and session clustering in our econometric models to control for this learning effect.

3.5. Estimation Strategy

Since each farmer has to make 18 binary choices, we have a typical panel structure of 205 time series and 18 sets of data.

$$x_{it}^{*} = \alpha_i + Z_{it}.\ \beta + \mu_{it} \qquad i \in [1,205] \quad t \in [1,18] \tag{3}$$

$$x_{it} = 1(x_{it}^{*} > 0) \tag{4}$$

where x_{it}^{*} is the latent variable of insurance uptake and x_{it} is the binary variable of insurance uptake; α_i is the individual effect of farmer i and Z_{it} is the vector of explanatory variables. Let Φ be the cumulative distribution function of observations,

$$p(x_{it} = 1 \mid Z_{it}, \alpha_i) = \Phi(\alpha_i + Z_{it}.\ \beta) \tag{5}$$

Given the experimental nature of our data, the variables of interest are exogenous and uncorrelated with fixed effects. Because linear estimations provide converging and unbiased estimators (Angrist and Pischke, 2008), we show the results of linear regressions in section 4 and provide robustness checks under nonlinear specifications, in the Appendix, section 6.4.

4. Empirical Results

4.1. Overall Insurance Demand

Table 5 shows the summary statistics of the insurance games.

Overall, we obtain high insurance take-up rates, on average 80% for the actuarially fair rate and 67% with a loading factor of $m = 1.5$ (Table 5), comparable with other similar real earnings games involving contextualized agricultural insurance among farmers (Petraud et al., 2014; Norton et al., 2014) or non-farmers (Laury et al., 2009; Slovic et al., 1977). Mcintosh et al., 2013) compared a survey-based hypothetical willingness to pay for insurance with actual uptake and found that stated and actual demand are very poorly correlated. Although our experiment is incentivised, it cannot be used to determine the magnitude of the effect of drought frequency on insurance take up in real life. The relatively high adoption rate in our experiment, required to increase the precision of marginal effects, should not be used as an indicator of real life insurance attractiveness. Take-up rates for all values of the parameters of interest (m, r and p), i.e. in each of the 18 games, are available in Table 7.

These take-up rates are much higher than in empirical non-experimental survey pilots[4]. Higher take-up in experiments than in pilots of real insurance supply seem to be a rather general feature, found in comparable studies with high take-up or willingness to pay, such as Petraud et al. (2014); Norton et al. (2014) and Serfilippi et al. (2018). This discrepancy may be due to the fact that many practical issues such as seasonal liquidity constraint or mistrust in the insurer are ignored in experimental set-ups.

4.2. Individual Insurance Demand

We estimate the relative role of the determinants of index-based insurance demand using different linear panel estimations: with random and fixed effects (Table 6). Fixed effects allows to control for the specificity of each village (column 2), individual (column 3), game (18 per individual, column 4) and session (2 per individual, column 5).

Because there may be longitudinal effects, for instance if a learning effect exists, wealth effects or any psychological effect due to pay off announcement, we introduce game fixed effects in addition to individual fixed effect. In particular, if a learning effect exists at each step of the experiment, its average value should be embedded in game fixed effects. Session fixed effects were introduced to control for individual specific learning across sessions. Similarly, although payments occurred at the end of the experiment, farmers could mentally compute their gain after the first session, and play the second one with greater wealth. We cannot exclude the possibility that this wealth effect is linked to loading factor increases. The session effect tends to decrease this bias.

[4] See section 1.

Table 3
Insurance contract characteristics and expected gains from lottery games.

game (#)	load. fact.	basis risk	drought freq.	premium (cfaF)	outcome (cfaF)					expec. gains (cfaF)	
					not insured		insured			not insured	insured
	m	r	p	P	rain	drought	rain	drought			
								indemn.	no indemn.		
					$(1-p)$	p	$(1-p)$	$(1-r)p$	rp		
1	1	0	1/20	40	800	0	760	760	−40	760	760
2	1	0	2/20	80	800	0	720	720	−80	720	720
3	1	0	7/20	280	800	0	520	520	−280	520	520
4	1	1/5	1/20	30	800	0	770	770	−30	760	760
5	1	1/5	2/20	60	800	0	740	740	−60	720	720
6	1	1/5	7/20	220	800	0	580	580	−220	520	520
7	1	2/5	1/20	20	800	0	780	780	−20	760	760
8	1	2/5	2/20	50	800	0	750	750	−50	720	720
9	1	2/5	7/20	170	800	0	630	630	−170	520	520
10	1.5	0	1/20	80	800	0	720	720	−80	760	720
11	1.5	0	2/20	160	800	0	640	640	−160	720	640
12	1.5	0	7/20	560	800	0	240	240	−560	520	240
13	1.5	1/5	1/20	60	800	0	740	740	−60	760	730
14	1.5	1/5	2/20	130	800	0	670	670	−120	720	650
15	1.5	1/5	7/20	450	800	0	350	350	−450	520	290
16	1.5	2/5	1/20	50	800	0	750	750	−40	760	730
17	1.5	2/5	2/20	100	800	0	700	700	−100	720	670
18	1.5	2/5	7/20	340	800	0	460	460	−340	520	350

Table 4
Insurance contracts offered by villages.

Sessions	Games	N villages	N prod	N obs.
Actuarially fair (m = 1)	1 to 9	9	205	1841
Loading factor (m = 1.5)	10 to 18	6	130	1168

Note: insurance with m = 1.5 could not be played in 3 out of 9 villages.

Table 5
Descriptive statistics of the insurance games.

Sessions	Obs	Mean	Std. Dev.	Min	Max
Take-up if m = 1	1841	0.81	0.39	0	1
Take-up if m = 1.5	1168	0.67	0.47	0	1

We control for heteroscedasticity by clustering at the individual and session level. In the case of session clustering (column 5 of Table 6), because the number of clusters was low (9), we use the Wild bootstrap method for a small number of clusters proposed by Cameron et al. (2008). With this model, the effect of the loading factor (m) change is included in the session fixed effect and is thus not reported.

Our main empirical result is that increasing drought frequency significantly decreases insurance take-up, this result being robust to different specifications (columns 1 to 5). The negative effect of p indeed holds both for random and fixed effects models and stands for specifications with individual (column 1 to 4) and sessions clustering (column 5). As robustness checks, we ran additional nonlinear model specifications, available in Appendix (Table 8 section 6.4), including both probit and logit regressions. Linear panel regressions, as well as

Table 6
Drivers of insurance take up: linear panel estimations.

	(1)	(2)	(3)	(4)	(5)
	RE	RE	FE	FE	FE
m	-0.211^{***}	-0.208^{***}	-0.208^{***}	-0.418^{***}	
	(0.0491)	(0.0518)	(0.0504)	(0.098)	
p	-0.235^{***}	-0.236^{***}	-0.235^{***}	-0.431^{**}	-0.248^{**}
	(0.0542)	(0.0592)	(0.0584)	(0.177)	(0.110)
					[0.0240]
r	-0.0909^{**}	-0.0908^{**}	-0.0909^{**}	0.154	−0.0809
	(0.0437)	(0.0400)	(0.0396)	(0.115)	(0.0664)
					[0.2382]
Constant	1.066^{***}	0.976^{***}	1.059^{***}	0.787	0.811^{***}
	(0.0637)	(0.0965)	(0.0662)	(0.715)	(0.0319)
Fixed-effects	No	Village	Ind.	Ind. & game	Ind. session
Observations	3009	3009	3009	3009	3009

Bootstrapped standard errors in parentheses, with individual (columns 1 to 4) and session (column 5) clustering. P-values from the distribution of Wild bootstrap t-statistics in brackets, with session clustering (column 5).
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

nonlinear panel estimations, validate the theoretical predictions that increasing the loading factor or the basis risk significantly reduces insurance take-up, in accordance with previous studies (; Karlan et al., 2014; Clarke, 2016; Giné et al., 2008; Giné and Yang, 2009; Cole et al., 2013).

The amplitude of the negative estimated impact of m should be treated with caution when considering the potential effect of learning during the experiment. Although training sessions were played before incentivised sessions, it may be that farmers' understanding was deeper during the second session with a higher loading factor, potentially altering their attitudes and notably their sensitivity to parameter changes.

We establish that the demand for insurance decreases with drought frequency, this result being robust to all specifications. In the trade-off between smoothing income and maintaining a higher income average, our result indicates that the second effect tends to dominate the first one as the drought frequency increases. It is consistent with the right side of the inverted U curve. Moreover, the amplitude of the negative effect of p is high and overpasses the impact of basis risk.

We have attempted to check whether drought frequency had a positive impact on insurance take up for lower values of drought frequency (in addition to their negative impact for greater values of drought frequency), as predicted in the theoretical model. Unfortunately, this attempt does not lead to a clear conclusion, in particular in the longitudinal effects specifications (see Table 10 of section 6.4 in Appendix).

Basic individual characteristics of farmers (i.e. sex and age) and households (members, number of cattle) were found to be non-significant (see Appendix, section 6.4).

To sum up our empirical results, demand for index-based insurance decreases with the probability of drought for high-probability droughts. This extends existing results on low-probabilities of shocks (Slovic et al., 1977; Mcclelland et al., 1993) to higher risk probabilities. The fact that the demand for index-based insurance depends on the probability of the insured risk challenges future index-based insurance contracts. Insurers willing to develop index-based drought insurance products in developing countries should bear in mind that: (1) drought insurance is only attractive to farmers under certain climatic contexts, with relatively low drought frequency (in a context of climate change, the attractiveness of such insurance is reduced if drought becomes more frequent); and (2) the drought frequency of insurance products should be chosen as a function of both basis risk and loading factor.

5. Conclusion

In this article we highlight that the low uptake of index-based insurance in developing countries may be partly due to the high probability of shocks. For damages of a given magnitude, there is an optimal damage frequency for which farmers' willingness to take out insurance is maximal. Our analytical and empirical findings suggest that beyond a certain threshold, demand for drought insurance decreases when drought frequency increases, all the more so as loading factor and basis risk are high.

Therefore, in addition to the low probability risk issue observed by many authors (e.g. in the context of earthquakes or floods), there may be a high probability risk issue, in the case of shocks like droughts, where damage remains significant as droughts tend to be more frequent. In a nutshell, since climate change may increase the probability of a given shock, it could hinder future individual adoption of private drought insurance. The optimal drought frequency depends on the basis risk and the loading factor. In our model this optimal frequency is reduced under basis risk, but we could not provide empirical validation of this theoretical feature.

Our experimental results must be seen through the lens of experimental economics, often associated with limitations on external validity. The amounts at stake in the experiment are lower than the amounts at stake in real life, and take-up decisions in real life may be subject to more complex constraints and incentives. The main interest of our experiment is that the marginal effects of drought frequency on take-up, revealed in the experiment, could explain some of the real life observations of low adoption of insurance. Three parameter changes are introduced into our experiment, and we consider a unique magnitude of loss, which is fixed and corresponds to a unique drought type, fully covered by the insurance. Our work does not consider other factors limiting insurance take-up, such as liquidity constraint or income diversification and the inhibiting role of drought frequency on insurance demand should probably be confronted to competing factors. The role of subjective probabilities and ambiguity on insurance demand has also been tested by Visser et al. (2019) and Belissa et al. (2019). Combination of subjective weighted probabilities and perception of actual changes in drought probabilities could be a potential follow up to our work.

Moreover, climate change in the Sahel may also be accompanied by more severe, though still infrequent, droughts, which are not within the scope of our analysis. Future research could address such questions by comparing different types of droughts that may occur in the near future, considering the negative relationship between the probability and the magnitude of the damage.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This paper is produced by the INRAE and CIRAD Economic Departments. It has benefited from funding from the European Union under the FARMAF project, grant n° 2011/260-875).

Appendix A. Appendix

A.1. Location of Villages in Burkina Faso

Lab-in-the-field experiments took place in 9 villages in Burkina Faso, which location is shown on the following map (Fig. 5).

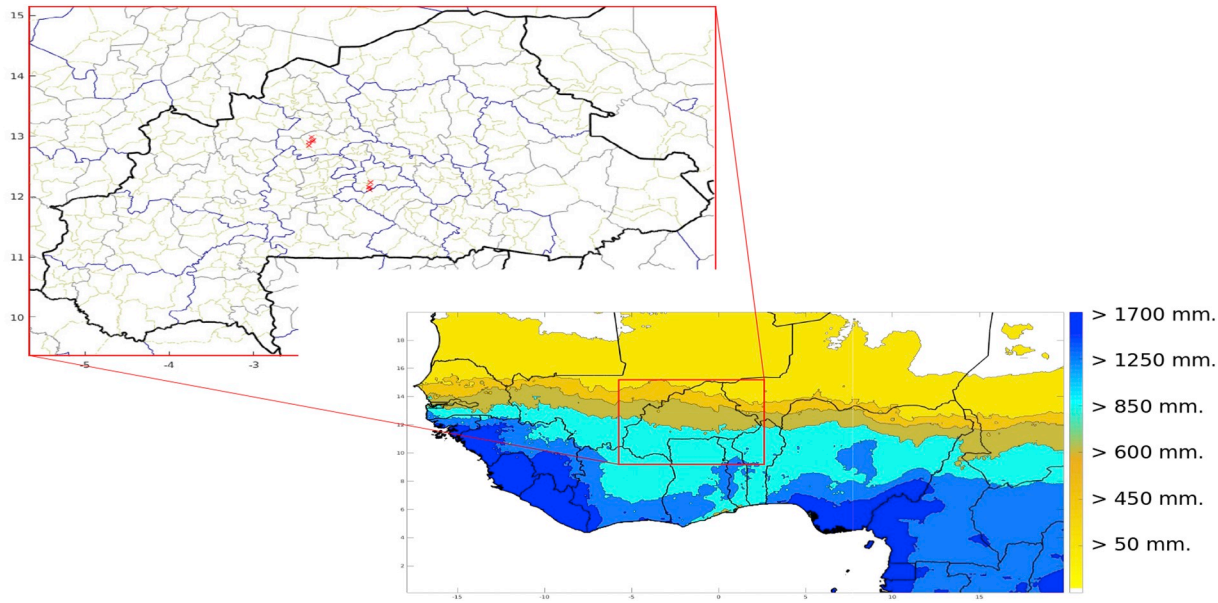


Fig. 5. Average annual cumulative rainfall levels (50, 450, 600, 850, 1250 and 1700 mm isohyets, CHIRPS data, 0.05 decimal degree resolution, 2000–2015, Funk et al. (2015)) and administrative units of Burkina Faso (*départments*: grey lines, *régions*: blue lines). The field experiment took place in nine villages (red crosses), 5 in Yako department (North Region) and 4 in Komsilga department (Center region). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A.2. Propositions and Proofs of the Model

Proposition 1.
If $m > \frac{u(y)-u(y-L)}{Lu'(y)}$, $\Delta EU \leq 0$ *(nil in* $p = 0$ *and increasingly negative as* p *increases).*
Proof.
First note that $\frac{\partial \Delta EU}{\partial p} = u(y) - u(y-L) - mLu'(y-mpL)$. In $p = 0$, $\frac{\partial \Delta EU}{\partial p} < 0$ if and only if $m > \frac{u(y)-u(y-L)}{Lu'(y)}$. Furthermore, it is clear from (1) that $\Delta EU = 0$, in $p = 0$. Finally, check that $\frac{\partial^2 \Delta EU}{\partial p^2} = m^2L^2u''(y-mpL) < 0$.

As a consequence, if $m > \frac{u(y)-u(y-L)}{Lu'(y)}$, ΔEU is nil and decreasing with p in $p = 0$, concave in $[0,1]$, this implies that $\forall p > 0$, $\Delta EU < 0$.
Proposition 2.
If $1 \leq m < \frac{u(y)-u(y-L)}{Lu'(y)}$ *and* $r = 0$, ΔEU *is an inverted u-shaped curve as* p *varies, with the following properties:*

ΔEU *is nil in* $p = 0$*, increasing with* p *in* $\left[0, p^* = \frac{y - u'^{-1}\left(\frac{u(y)-u(y-L)}{mL}\right)}{mL}\right]$*, decreasing with* p *in* $[p^*;1]$*, and negative in* $p = 1$ *if and only if* $m > 1$.

As a corollary, if $1 < m < \frac{u(y)-u(y-L)}{Lu'(y)}$*, there exists* $p^{**} \in]p^*; 1[$ *such that expected gains are negative in* $[p^{**};1]$*, with* $p^{**} = \frac{u(y-mp^{**}L)-u(y)}{u(y-L)-u(y)}$.
Proof.
The proof of proposition 1 implies that if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, $\frac{\partial \Delta EU}{\partial p} > 0$ for $p = 0$.
In $p = 1$, $\Delta EU = u(y - mL) - u(y - L)$, which is strictly negative if and only if $m > 1$.
These three properties together (concavity on $[0,1]$, positive slope in 0, $\Delta EU = 0$ in $p = 0$ and $\Delta EU < 0$ in $p = 1$) guarantee the inverted U-shape of ΔEU in p, and the existence of an optimal value of $p^* \in]0; 1[$ such that $p^* = \frac{y - u'^{-1}\left(\frac{u(y)-u(y-L)}{mL}\right)}{mL} < 1$.
Proposition 3.
$\forall r \in [0; 1[$*, if* $m < \frac{u(y)-u(y-L)}{Lu'(y)}$*,* ΔEU *is an inverted u-shape function of* p *in* $[0,1]$.
As a consequence, there is a unique $p^* \in]0; 1[$ such that $p^* = argmax(\Delta EU)$.
Proof.
First note that if $p = 0$, $\Delta EU = 0$. Furthermore, replacing P by $mp(1 - r)L$ in Eq. (1), and deriving with regard to p leads to

$$\frac{\partial \Delta EU}{\partial p} = u(y) - u(y-L) - r[u(y - mpL(1-r)) - u(y - mpL(1-r) - L)] \\ - (1-r)mL[pru'(y - mpL(1-r) - L) + (1-pr)u'(y - mpL(1-r))] \tag{6}$$

In $p = 0$, $\frac{\partial EU}{\partial p} = (1-r)[u(y) - u(y-L) - mLu'(y)]$.

Given that $0 \leq r \leq 1$, ΔEU increases with p in $p = 0$ if and only if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, as in the case with no basis risk.
We then check that ΔEU is concave in p

$$\frac{\partial^2 \Delta EU}{\partial p^2} = rm(1-r)Lu'(y - mp(1-r)L) + rm(1-r)Lu'(y - mp(1-r)L) + (1-rp)m^2(1-r)^2L^2u''(y - mp(1-r)L) - m(1-r)Lru'(y - mp(1-r)L - L) - rm(1-r)Lu'(y - mp(1-r)L - L) + rpm^2(1-r)^2L^2u''(y - mp(1-r)L - L) \quad (7)$$

Or after rearranging,

$$\frac{\partial^2 \Delta EU}{\partial p^2} = 2rm(1-r)L\,[u'(y - mp(1-r)L) - u'(y - mp(1-r)L - L)] + (1-rp)m^2(1-r)^2L^2u''(y - mp(1-r)L) + rpm^2(1-r)^2L^2u''(y - mp(1-r)L - L) \quad (8)$$

Concavity of u ensures that $u'(y - mp(1-r)L) < u'(y - mp(1-r)L - L)$ and that $u'' < 0$. We thus have $\frac{\partial^2 \Delta EU}{\partial p^2} < 0$.

Then we show that in $p = 1$, $\Delta EU < 0$.

$$\Delta EU = (1-r)u(y-P) + ru(y-P-L) - u(y-L).$$

If $L < P$, $u(y-L-P) < u(y-P) < u(y-L)$ and $u(y-L)$ is then greater than any weighted mean of $u(y-P)$ and $u(y-P-L)$, thus $(1-r)u(y-P) + ru(y-P-L) < u(y-L)$.

If $L \geq P$, $u(y-L-P) < u(y-L) < u(y-P)$ and because u is concave, $u(y-L)$ is greater than any weighted mean of $u(y-L-P)$ and $u(y-P)$, thus $(1-r)u(y-P) + ru(y-P-L) \leq u(y-L)$.

Thus, ΔEU is nil in $p = 0$, increasing with p in $p = 0$ provided $m > \frac{u(y)-u(y-L)}{Lu'(y)}$, and concave on [0,1], and reaches negative values before $p = 1$. This garantees that $\forall p \in [0;1]$, if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, expected gain from insurance has an inverted U-shape as p varies.

The global analysis of the variation of ΔEU when r varies on $[0,1]$ is not trivial because ΔEU is not concave in r without more assumptions. For instance ΔEU is decreasing in r for $r = 0$, $\forall p$ but increasing in r in $r = 1$, $p = 1$, which indicates a change in concavity of ΔEU with respect to r for $p = 1$.

We can nevertheless provide a sufficient condition for ΔEU to be decreasing in r on $[0;1]$. If u is a CRRA function of parameter ρ, $\frac{\partial \Delta EU}{\partial r} < 0$ is equivalent to

$$\left(\frac{y-P}{y-P-L}\right)^{\rho} \frac{(1-\rho)rpmL + y - P - L}{(1-rp)(1-\rho)mL - y + P} < -1$$

a sufficient condition for this expression to be true is

$$m < \frac{1}{1-\rho}$$

A.2.1. Expected Effects

If $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, three types of impact are expected:

$$\frac{\partial prob(\widetilde{x}_i = 1)}{\partial m} < 0$$

$$\frac{\partial prob(\widetilde{x}_i = 1)}{\partial p} < 0 \quad \text{iff} \quad p > p^*$$

$\frac{\partial prob(\widetilde{x}_i = 1)}{\partial r} < 0$ if $u(r,m,p,L)$ is a CRRA utility function of parameter ρ and $m < \frac{1}{1-\rho}$.

The partial effect of m is straightforward and the partial effect of p simply derives from the fact that $prob(\widetilde{x}_i = 1) = prob(\Delta EU + \varepsilon_i > 0)$ which is decreasing with p if and only if ΔEU is decreasing with p, i.e. when $p > p^*$.

A.3. Experimental Protocol

A.3.1. Introductory Comments

You have the opportunity to take part in a field experiment about risk and drought insurance. Drought insurance is an agreement between a farmer and an insurer whereby the farmer pays a premium in May and, if drought occurs, he receives an indemnity in November. We will describe 18 types of insurance, and for each one, you have to decide whether you want to take out the insurance and pay the premium. A the end of the experiment, you will get the amount of money that is defined in these contracts, depending on the choices you made in these games, and whether drought occurred or not. Of the 18 choices, two will be randomly selected, and these two choices will determine how much money you will receive. The amount you will receive will depend on your choices, but also on random factors, since the occurrence of drought or rain is random. This money will be yours.

Do you have any questions?

If you have questions during the games, raise your hand and we will answer you. It is important that you do not talk with one another once the game has started. There is no right or wrong answer, the money you will obtain will depend upon your choices and the random draws. It is important that you do not try to look at your neighbour's sheet.

The games will last two hours. If you think that you cannot stay for two hours, please tell us now.

A.3.2. Instructions Given to Farmers: Training Examples

Before starting the experiment, we will give you two examples. In this game, we consider that you produce maize and you have the choice whether or not to take out insurance against drought affecting your maize production.

In the example, you cultivate half a hectare of maize and your yield is 8 bags of 100 kg if the rainfall is good and 0 bags if there is a drought. Each bag you produce is sold for 10,000 cfaF. If the rainfall is good, you earn 80,000 cfaF and if there is a drought you earn zero.

In the first example, drought is rare. There is a drought once every 20 years. In May, you decide whether to take out the insurance, in which case you will pay a premium of 4000 cfaF, or not to pay the premium. Then we must determine whether there is rain or drought. To do this, we put one orange ball and 19 white balls in a bowl. A blindfolded child will pick one ball.

If he picks a white ball, the season is rainy and the harvest is good. If you have paid the insurance premium (4000 cfaF) the harvest value is 80,000 cfaF and your income is thus 76,000 cfaF. If you did not pay for the insurance, your income is 80,000 cfaF.

If the child picks the orange ball, the season is dry and the harvest is nil. If you have paid the premium (4000 cfaF) you get an indemnity to compensate for your loss (80,000 cfaF), so that your income is 76,000 cfaF. If you did not pay the premium, you get zero.

The choice you have to make is: “do you want to take out this insurance?”

In the second example, the drought is still rare, but there is a small risk that the insurer makes a mistake and does not pay the indemnity. There is one drought every 20 years and the insurer can make a mistake on two occasions out of ten. This means that if there is a drought and if you have paid the premium, there is a 2 in 10 chance that the insurer does not pay the indemnity. This is because, for example, the insurer thinks that there has been rain but in reality, the rain has not fallen on your field or not during the useful period. The insurance premium is then cheaper (3200 cfaF) because the insurer knows that he might make a mistake. First, you decide whether or not to pay the insurance premium, then the child picks a ball from the bowl to determine whether the weather is rainy or dry.

If he picks a white ball, there is rain. Everybody harvests 80,000 cfaF-worth of maize. The income of those who have paid the premium is 76,800 cfaF, whereas those who have not paid the premium receive 80,000 cfaF.

If the child picks an orange ball, there is a drought. The harvest is zero. Those who did not take the insurance get zero. The income of those who took the insurance depends on the result from the bucket, which contains two red balls and 8 black balls. If the child picks a red ball, those who have paid the insurance get zero from the insurer, so that they have lost 3200 cfaF. If the child picks a black ball, the income of those who have paid the insurance is 76,800 cfaF.

The choice you have to make is: “do you want to take out this insurance?”. Do you have any questions? Has everyone understood everything?

A.3.3. Instructions Given to Farmers: Incentivised Insurance Experiment

Now, the game is for real money. For each type of insurance, we will tell you the amount of the premium, the frequency of drought, and the risk that the insurer makes a mistake. For each type of insurance, you decide whether you want to pay the premium or not. If you want to pay the premium, you make a cross in the blue column. If you do not want to pay the insurance, you make a cross in the yellow column. There are 18 choices in this serie, for 18 types of insurance. At the end of the series, a child will pick two of the 18 numbered balls from this cage. The numbers on these two balls will indicate the numbers of the choices for which you will receive money. Then, the child will pick one ball from the bowl to determine whether the rainfall was good, and one ball from the bucket to determine whether you get the indemnity from the insurer. You will then receive the amount of money corresponding to your decision whether or to to take out insurance. In the previous examples, the price of a bag was 10,000 cfaF. In the experiment, it is 100cfaF. In the first example above, this means that the harvest is 800 cfaF instead of 80,000 cfaF if there is rain, and the premium is 40 cfaF instead of 4000 cfaF.

Do you have any questions? Has everyone understood everything?

- Insurance 1. Drought occurs once every twenty years, and the insurer makes no mistakes. The premium is 40 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 760 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance get 760 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?
- Insurance 2. Drought occurs twice every twenty years, and the insurer makes no mistakes. The premium is 80 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 720 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance receive 720 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?
- Insurance 3. Drought occurs seven times every twenty years, and the insurer makes no mistakes. The premium is 280 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 520cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance receive 520 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?
- Insurance 4. Drought occurs once every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 30 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 770 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 30cfaF and if the child picks a black ball, they receive 770 cfaF. Do you want to pay the premium and take out the insurance?
- Insurance 5. Drought occurs twice every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 60 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 740 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 60cfaF and if the child picks a black ball, they receive 740cfaF. Do you want to pay the premium and take out the insurance?
- Insurance 6. Drought occurs seven times every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 220 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 580 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 220 cfaF and if the child picks a black ball, they receive 580 cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 7. Drought occurs once every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 20 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 780 cfaF, and those who do not take insurance receive 800cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 20 cfaF and if the child picks a black ball, they receive 780 cfaF. Do you want to pay the premium and take out the insurance?
- Insurance 8. Drought occurs twice every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 50 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 750 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 50cfaF and if the child picks a black ball, they receive 750 cfaF. Do you want to pay the premium and take out the insurance?
- Insurance 9. Drought occurs seven times every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 170 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 630 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 170 cfaF and if the child picks a black ball, they receive 630 cfaF. Do you want to pay the premium and take out the insurance?

Nine similar choices are made in the case where the insurer makes a profit (loading factor $m = 1.5$). The 18 insurance products are summarised below.

Table 7
Premiums and loading factors, basis risks and drought frequencies.

Game number	Loading factor	Basis risk	Drought frequency	Premium (cfaF)	Outcome					Average Δ Expected gain	Average take-up
					not insured		insured				
	m	r	p	P	Rain	Drought	Rain	Drought			
								Indemnity	No indemnity		
1	1	0	1/20	4000	80,000	0	76,000	76,000	−4000	0	0.82
2	1	0	2/20	8000	80,000	0	72,000	72,000	−8000	0	0.83
3	1	0	7/20	28,000	80,000	0	52,000	52,000	−28,000	0	0.82
4	1	1/5	1/20	3000	80,000	0	77,000	77,000	−3000	0	0.82
5	1	1/5	2/20	6000	80,000	0	74,000	74,000	−6000	0	0.80
6	1	1/5	7/20	22,000	80,000	0	58,000	58,000	−22,000	0	0.78
7	1	2/5	1/20	2000	80,000	0	78,000	78,000	−2000	0	0.78
8	1	2/5	2/20	5000	80,000	0	75,000	75,000	−5000	0	0.80
9	1	2/5	7/20	17,000	80,000	0	63,000	63,000	−17,000	0	0.80
10	1.5	0	1/20	8000	80,000	0	72,000	72,000	−8000	−4000	0.82
11	1.5	0	2/20	16,000	80,000	0	64,000	64,000	−16,000	−8000	0.74
12	1.5	0	7/20	56,000	80,000	0	24,000	24,000	−56,000	−28,000	0.53
13	1.5	1/5	1/20	6000	80,000	0	74,000	74,000	−6000	−3000	0.68
14	1.5	1/5	2/20	13,000	80,000	0	67,000	67,000	−13,000	−6000	0.71
15	1.5	1/5	7/20	45,000	80,000	0	35,000	35,000	−45,000	−23,000	0.55
16	1.5	2/5	1/20	5000	80,000	0	75,000	75,000	−5000	−2000	0.70
17	1.5	2/5	2/20	10,000	80,000	0	70,000	70,000	−10,000	−5000	0.70
18	1.5	2/5	7/20	34,000	80,000	0	46,000	46,000	−34,000	−17,000	0.58

A.4. Robustness Checks

A.4.1. Nonlinear Estimations

We decline, as robustness checks, our analysis using two main econometric specifications in panel: a probit random effects model with bootstrapped standard errors (Table 8 columns 1 and 2) including Mundlak-Chamberlain's corrections and a logit model with individual fixed effects (Table 8 column 3). In column 2 of Table 8, village fixed effects are added to the estimation.

We first estimate a probit random effects panel regression as in Laury et al. (2009), with bootstrapped standard errors. The MLE of this model is the efficient-unbiased estimation method in case of no correlation between regressors and fixed effects. However, Hausman's test of no correlation between regressors and individual effects is significantly rejected and this rejection is robust to specification changes, which raises doubts about the random effect specification. Mundlak-Chamberlain's approach can be used to no longer apply the random effect assumption of no correlation between individual effects and regressors (Chamberlain, 1984). The correlation is supposed to have a given structure, for instance a linear function of the mean of the regressors for each time series, as in Mundlak (1978):

$$\alpha_i | Z_{it} \sim \mathcal{N}(\psi + \overline{Z}_i \xi, \sigma^2) \tag{9}$$

where $\overline{Z}_i$ is a vector of individual mean values of each regressor Z_{it}.

Secondly, we estimate a conditional logit model which eliminates the fixed effect terms in the estimate of covariates. The covariate estimates are then unbiased. This method works with a logistic functional form of the error term distribution and not with a normal one.

With both estimators, we estimate a linear model:

$$x_{it}^* = \alpha_i + \beta_0 + \beta_1 m_t + \beta_2 p_t + \beta_3 r_t + C_i . \gamma + \mu_{it} \tag{10}$$

$$x_{it} = 1 \quad (x_{it}^{*} > 0) \tag{11}$$

where C_i is the vector of individual characteristics of farmer i, only used in the random effects estimations. When this vector is introduced in the fixed effect model, multi-colinearity makes estimation impossible.

Table 8
Drivers of insurance take up: nonlinear estimations.

	(1)	(2)	(3)
	Probit RE	Probit RE	Logit FE
m	−1.426***	−1.403***	−2.370***
	(0.367)	(0.310)	(0.543)
p	−1.417***	−1.417***	−2.402***
	(0.400)	(0.284)	(0.445)
r	−0.506**	−0.505**	−0.886**
	(0.249)	(0.234)	(0.357)
Constant	3.237***	2.751***	.
	(0.396)	(0.568)	.
lnsig2u	1.088***	0.942***	.
	(0.146)	(0.170)	.
Observations	3009	3009	1596
Prob > chi2	.	.	0.0000
Village fixed effects	No	Yes	No

Bootstrapped standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$.

A.4.2. Household Characteristics

The results of linear panel specifications show no stable impact of household characteristics on adoption rates (Table 9). We control for household characteristics and for productive assets, and notably for age and education (ability to read and secondary school attendance), number of members of the household, total acreage and number of cattle.

A.4.3. Drivers of Insurance Take up for Low and High Values of Drought Frequencies in a Linear Panel Estimation

The inverted u shape of the effect of p on the take up, cannot directly be tested in our setting, but we can try to distinguish the effect of p for relatively low values of p and for relatively high values of p. We constructed two binary variables, $p_1 = p$ when $p < 7/20$ and zero if $p = 7/20$, and $p_2 = p$ when $p > 1/20$ and zero if $p = 1/20$. The results are presented in Table 10. The effect of drought frequency on insurance take-up is not monotonic. The effect of p_1 is the shift from a high frequency (7/20) to lower frequencies and it appears to have no clear effect or a positive effect on take up, (especially after controlling for session-specific variance through session clustering (column 4, Table 10). By contrast, the shift from a low frequency (1/20) to higher frequencies (p_2) has a clearly negative impact on take up. This cannot be taken as a confirmation of our theory of a inverted u curve, but mostly a validation that the negative effect occurs for higher frequencies.

Table 9
Drivers of insurance take up: linear estimations, control for households characteristics.

	(1)	(2)	(3)	(4)	(5)
	RE	RE	RE	RE	RE
m	−0.117**	−0.0951**	−0.117*	−0.117*	−0.0951**
	(0.0505)	(0.0468)	(0.0671)	(0.0683)	(0.0555)
p	−0.245***	−0.246***	−0.245**	−0.245**	−0.246**
	(0.0540)	(0.0551)	(0.109)	(0.117)	(0.117)
r	−0.0852**	−0.0843*	−0.0852	−0.0852	−0.0843
	(0.0470)	(0.0478)	(0.0652)	(0.0696)	(0.0698)
Sex	0.0491	0.0566	0.0491	0.0491	0.0566
	(0.0500)	(0.0488)	(0.0499)	(0.0429)	(0.0381)
Age	0.00338*	0.00260	0.00338***	0.00338**	0.00260**
	(0.00174)	(0.00179)	(0.00126)	(0.00145)	(0.00124)
Ability to read	−0.0170	−0.0195	−0.0170	−0.0170	−0.0195
	(0.0454)	(0.0457)	(0.0427)	(0.0395)	(0.0308)
Secondary school attendance	−0.0976	−0.108	−0.0976	−0.0976	−0.108*
	(0.0950)	(0.0930)	(0.107)	(0.0646)	(0.0624)
Household members	−0.000466	0.00115	−0.000466	−0.000466	0.00115
	(0.00443)	(0.00453)	(0.00350)	(0.00385)	(0.00511)
Cultivated area	−0.00797	−0.0136	−0.00797	−0.00797	−0.0136
	(0.00884)	(0.00964)	(0.00858)	(0.0128)	(0.0145)
Number of cattle	0.00561	0.00386	0.00561	0.00561**	0.00386**
	(0.0125)	(0.0159)	(0.0132)	(0.00263)	(0.00178)
Constant	0.787***	0.699***	0.787***	0.787***	0.699****
	(0.129)	(0.144)	(0.103)	(0.103)	(0.112)

(continued on next page)

Table 9 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	RE	RE	RE	RE	RE
Fixed Effects	*No*	*Village*	*No*	*No*	*Village*
Level of clustering	Individual	Individual	Village	session	session
Observations	2928	2928	2928	2928	2928

Standard errors in parentheses, robust to clustering.
* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 10
Drivers of insurance take up for low and high values of p: linear panel estimations.

	(1)	(2)	(3)	(4)	(5)
	RE	RE	FE	FE	FE
m	−0.211***	−0.208***	−0.208***	−0.418***	
	(0.0508)	(0.0489)	(0.0505)	(0.091)	
*p*1	0.232*	0.231*	0.230*	0.424	0.202
	(0.138)	(0.134)	(0.129)	(0.324)	(0.159)
					[0.2162]
*p*2	−0.161***	−0.161***	−0.162***	−0.269*	−0.179*
	(0.0487)	(0.0492)	(0.0557)	(0.138)	(0.0939)
					[0.0761]
r	−0.0909*	−0.0908**	−0.0909**	0.154	−0.0809
	(0.0477)	(0.0443)	(0.0390)	(0.137)	(0.0695)
					[0.2573]
Constant	1.040***	0.950***	1.032***	0.786***	1.252***
	(0.0652)	(0.0897)	(0.0622)	(0.0337)	(0.187)
Fixed effects	No	Village	Individual	Ind. & game	Ind. × session
Observations	3009	3009	3009	3009	3009

Bootstrapped standard errors in parentheses, with individual (columns 1 to 4) and session (column 5) clustering.
P-values from the distribution of Wild bootstrap t-statistics in brackets, with session clustering (column 5).
* $p < .1$, ** $p < .05$, *** $p < .01$.

References

Angrist, J.D., Pischke, J.-S., 2008. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.
Belissa, T.K., Lensink, R., van Asseldonk, M., 2019. Risk and Ambiguity Aversion Behavior in Index-Based Insurance Uptake Decisions: Experimental Evidence from Ethiopia. Journal of Economic Behavior & Organization.
Cai, H., Chen, Y., Fang, H., Zhou, L.-A., 2009. Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment. Working Paper 15396. National Bureau of Economic Research.
Cai, J., De Janvry, A., Sadoulet, E., 2015. Social networks and the decision to insure. Am. Econ. J. Appl. Econ. 7, 81–108.
Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econ. Stat. 90, 414–427.
Carter, M.R., Cheng, L., Sarris, A., 2016. Where and how index insurance can boost the adoption of improved agricultural technologies. J. Dev. Econ. 118, 59–71.
Casaburi, L., Macchiavello, R., 2019. Demand and supply of infrequent payments as a commitment device: evidence from Kenya. Am. Econ. Rev. 109, 523–555.
Casaburi, L., Willis, J., 2018. Time versus state in insurance: experimental evidence from contract farming in Kenya. Am. Econ. Rev. 108, 3778–3813.
Chamberlain, G., 1984. Panel data. In: Griliches, Z., Intriligator, M.D. (Eds.), Handbook of Econometrics. 2. Elsevier, pp. 1247–1318 chap. 22.
Chambers, R.G., 1989. Insurability and moral hazard in agricultural insurance markets. Am. J. Agric. Econ. 71, 604–616.
Clarke, D.J., 2016. A Theory of Rational Demand for Index Insurance. American Economic Jounal: Microeconomics, forthcoming.
Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., Vickery, J., 2013. Barriers to household risk management: evidence from India. Am. Econ. J. Appl. Econ. 5, 104–135.
Conradt, S., Finger, R., Spörri, M., 2015. Flexible weather index-based insurance design. Clim. Risk Manag. 10, 106–117.
Dalhaus, T., Musshoff, O., Finger, R., 2018. Phenology information contributes to reduce temporal basis risk in agricultural weather index insurance. Sci. Rep. 8, 46.
Dercon, S., Gunning, J.W., Zeitlin, A., 2015. The demand for insurance under limited trust: Evidence from a field experiment in Kenya. Tech. rep. Centre for the Studies of African Economies, Oxford.
Dercon, S., Krishnan, P., 2000. Vulnerability, seasonality and poverty in Ethiopia. J. Dev. Stud. 36, 25–53.
Dercon, S., Hill, R.V., Clarke, D., Outes-Leon, I., Taffesse, A.S., 2014. Offering rainfall insurance to informal insurance groups: evidence from a field experiment in Ethiopia. J. Dev. Econ. 106, 132–143.
Doherty, N., Schlesinger, H., 1990. Rational insurance purchasing: consideration of contract nonperformance. Q. J. Econ. 55, 243–253.
Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al., 2015. The climate hazards infrared precipitation with stationsa new environmental record for monitoring extremes. Scientific Data 2, 150066.
Gaurav, S., Cole, S., Tobacman, J., 2011. A Randomized Evaluation of the Impact of Financial Literacy on Rainfall Insurance Take Up in Gujarat. Tech. rep. ILO/EUDN.
Giné, X., Yang, D., 2009. Insurance, credit, and technology adoption: field experimental evidence from Malawi. J. Dev. Econ. 89 (1–11), 0304–3878.
Giné, X., Townsend, R., Vickery, J., 2008. Patterns of rainfall insurance participation in rural India. World Bank Econ. Rev. 22, 539–566.
Gneezy, U., Imas, A., 2017. Lab in the field: Measuring preferences in the wild. In: Handbook of economic field experiments. 1. Elsevier, pp. 439–464.
Grislain-Letrémy, C., 2016. Natural Disasters: Exposure and Underinsurance. (Mimeo).
Hertwig, R., Barron, G., Weber, E.U., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol. Sci. 15, 534–539.
Jaspersen, J.G., 2016. Hypothetical surveys and experimental studies of insurance demand: a review. J. Risk Insurance. 83 (1), 217–255.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.
Karlan, D., Osei, R., . Osei-Akoto, I., Udry, C., 2014. Agricultural Decisions after Relaxing Credit and Risk Constraints. The Quarterly Journal of Economics.
Kousky, C., Cooke, R., 2012. Explaining the failure to insure catastrophic risks. The Geneva Papers on Risk and Insurance Issues and Practice 37, 206–227.
Kunreuther, H., Pauly, M., 2004. Neglecting disaster: why don't people insure against large losses? J. Risk Uncertain. 28, 5–21.
Kunreuther, H., Slovic, P., 1978. Economics, psychology, and protective behavior. Am. Econ. Rev. 68, 64–69.
Kunreuther, H., Novemsky, N., Kahneman, D., 2001. Making low probabilities useful. J. Risk Uncertain. 23, 103–120.
Laury, S.K., Mcinnes, M.M., Swarthout, J.T., 2009. Insurance decisions for low-probability losses. J. Risk Uncertain. 39, 17–44.
Leblois, A., Quirion, P., Sultan, B., 2014. Price vs. weather shock hedging for cash crops: ex ante evaluation for cotton producers in Cameroon. Ecol. Econ. 101, 67–80.
Mahul, O., 2001. Optimal insurance against climatic experience. Am. J. Agric. Econ. 83,

593–604.
Mcclelland, G.H., Schulze, W.D., Coursey, D.L., 1993. Insurance for low-probability hazards: a bimodal response to unlikely events. J. Risk Uncertain. 7, 95–116.
Mcintosh, C., Sarris, A., Papadopoulos, F., 2013. Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. Agric. Econ. 44, 399–417.
Mobarak, A.M., Rosenzweig, M.R., 2013. Informal risk sharing, index insurance, and risk taking in developing countries. Am. Econ. Rev. 103, 375–380.
Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica 69–85.
Norton, M.T., Turvey, C., Osgood, D., 2013. Quantifying Spatial Basis Risk for Weather Index Insurance. The Journal of Risk Finance.
Norton, M., Osgood, D., Madajewicz, M., Holthaus, E., Peterson, N., Diro, R., Mullally, C., Teh, T.-L., Gebremichael, M., 2014. Evidence of demand for index insurance: experimental games and commercial transactions in Ethiopia. J. Dev. Stud. 50, 630–648.
Panthou, G., Lebel, T., Vischel, T., Quantin, G., Sane, Y., Ba, A., Ndiaye, O., Diongue-Niang, A., Diopkane, M., 2018. Rainfall intensification in tropical semi-arid regions: the Sahelian case. Environ. Res. Lett. 13, 064–074.
Patt, A., Suarez, P., Hess, U., 2010. How do small-holder farmers understand insurance, and how much do they want it? Evidence from Africa. Global Environmental Change 20, 153–161 adaptive Capacity to Global Change in Latin America.
Petraud, J.P., Boucher, S., Carter, M., et al., 2014. Competing theories of risk preferences and the demand for crop insurance: Experimental evidence from Peru. In: document de travail, département de léconomie agricole et des ressources naturelles, Université de Californie à Davis.
Platteau, J.-P., De Bock, O., Gelade, W., 2017. The Demand for Microinsurance: A Literature Review. World Development.
Raschky, P.A., Schwarze, R., Schwindt, M., Zahn, F., 2013. Uncertainty of governmental relief and the crowding out of flood insurance. Environ. Resour. Econ. 54, 179–200.
Serfilippi, E., Carter, M., Guirkinger, C., 2018. Insurance contracts when individuals greatly value certainty: results from field experiments in Burkina Faso. National Bureau of Economic Research, 25026. https://doi.org/10.3386/w25026. http://www.nber.org/papers/w25026.
Slovic, P., Fischhoff, B., Lichtenstein, S., Corrigan, B., Combs, B., 1977. Preference for insuring against probable small losses: insurance implications. J. Risk Insurance 237–258.
Tadesse, M.A., Shiferaw, B.A., Erenstein, O., 2015. Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for sub-Saharan Africa. Agric. Food Econ. 3, 1–21.
Turvey, C.G., Nayak, G., 2003. The semivariance-minimizing hedge ratio. J. Agric. Resour. Econ. 100–115.
Tversky, A., Kahneman, D., 1992. Advances in prospect theory: cumulative representation of uncertainty. J. Risk Uncertain. 5, 297–323.
Vasilaky, K., Diro, R., Norton, M., Mccarney, G., Osgood, D., 2019. Can Education Unlock Scale? The Demand Impact of Educational Games on a Large-Scale Unsubsidised Index Insurance Programme in Ethiopia. J. Dev. Stud. 1–23.
Visser, M., Jumare, H., Brick, K., 2019. Risk Preferences and Poverty Traps in the Uptake of Credit and Insurance amongst Small-Scale Farmers in South Africa. Journal of Economic Behavior & Organization.

POURQUOI UNE RELATION POSITIVE ENTRE TAILLE DES EXPLOITATIONS ET PRODUCTIVITÉ AU BURKINA FASO ?

Yves Gérard Bazie, Tristan Le Cotty, Élodie Maitre D'hôtel, Damien Oula Ouattara, Audrier Sanou

Société française d'économie rurale | « Économie rurale »

2020/1 n° 371 | pages 37 à 58

ISSN 0013-0559

Article disponible en ligne à l'adresse :

https://www.cairn.info/revue-economie-rurale-2020-1-page-37.htm

Économie rurale
Agricultures, alimentations, territoires

371 | janvier-mars 2020
varia

Pourquoi une relation positive entre taille des exploitations et productivité au Burkina Faso ?

Why is there a positive relationship between farm size and productivity in Burkina Faso?

Yves Gérard Bazie, Tristan Le Cotty, Élodie Maitre D'hôtel, Damien Oula Ouattara et Audrier Sanou

Édition électronique
URL : http://journals.openedition.org/economierurale/7592
DOI : 10.4000/economierurale.7592
ISSN : 2105-2581

Éditeur
Société Française d'Économie Rurale (SFER)

Édition imprimée
Date de publication : 31 mars 2020
Pagination : 37-58
ISSN : 0013-0559

Distribution électronique Cairn

Référence électronique
Yves Gérard Bazie, Tristan Le Cotty, Élodie Maitre D'hôtel, Damien Oula Ouattara et Audrier Sanou, « Pourquoi une relation positive entre taille des exploitations et productivité au Burkina Faso ? », *Économie rurale* [En ligne], 371 | janvier-mars 2020, mis en ligne le 02 janvier 2022, consulté le 30 mars 2020. URL : http://journals.openedition.org/economierurale/7592 ; DOI : https://doi.org/10.4000/economierurale.7592

Pourquoi une relation positive entre taille des exploitations et productivité au Burkina Faso ?

Yves Gérard BAZIE • *Ministère de l'Agriculture, Ouagadougou, Burkina Faso*
Tristan LE COTTY, Élodie MAITRE D'HOTEL • *CIRAD, Montpellier, France*
Damien Oula OUATTARA, Audrier SANOU • *Ministère de l'Agriculture, Ouagadougou, Burkina Faso*

La productivité à l'hectare des céréales est plus importante dans les exploitations agricoles de grande taille au Burkina Faso. Cette relation positive va à l'encontre du constat dominant estampillé dans la littérature économique comme la « relation inverse entre taille et productivité ». Cet article analyse l'interdépendance entre les productions de maïs et de coton pour l'accès à l'engrais comme facteur explicatif de la relation positive. Un modèle de production inspiré de Feder (1985) est appliqué à la production du maïs sous contrainte de crédit. Il établit que le rendement du maïs augmente avec la surface totale de l'exploitation, à condition que cet accroissement se traduise par une levée de la contrainte de terre cultivable en coton. La validité empirique de ce modèle est testée par la mobilisation de données ménages, de prix et de données pluviométriques au Burkina Faso sur la période 1995-2012.

MOTS-CLÉS : *taille, productivité, engrais, Burkina Faso*

Why is there a positive relationship between farm size and productivity in Burkina Faso?

In Burkina Faso, grain productivity is higher in larger farms. This positive relationship goes against the dominant empirical finding known in the economic literature as the "inverse farm size-productivity relationship." This paper analyzes the interdependence between maize and cotton production for access to fertilizer as an explanatory factor for the positive relationship. A production model inspired by Feder (1985) is applied to the production of maize under credit constraints. It states that maize yield increases with the total area of the farm, provided that this increase translates into a lifting of the cultivable cotton land constraint. The empirical validity of this model is tested using a combination of household, price, and rainfall data for Burkina Faso over the 1995–2012 period. (JEL: Q12).

KEYWORDS: *size, productivity, fertilizer, Burkina Faso*

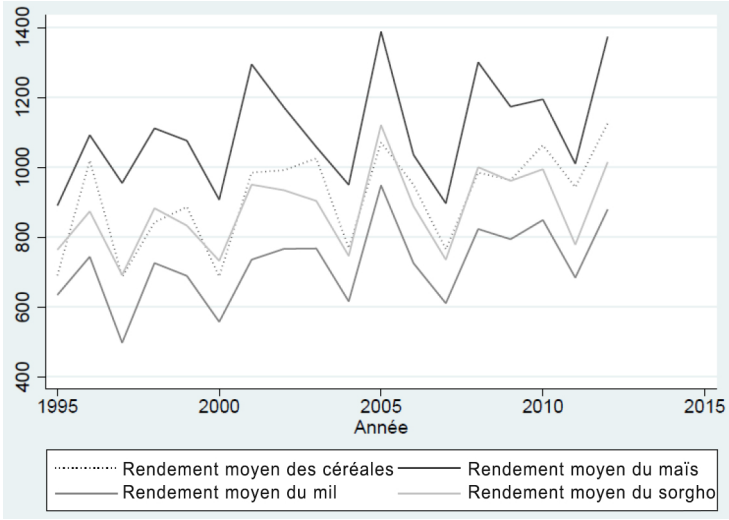
Introduction

1. Augmentation de la productivité des céréales

Les céréales représentent la majorité de la production agricole du Burkina Faso et correspondent aux deux tiers environ de l'apport calorique de la population burkinabè (FAOSTAT data). La production de céréales est donc déterminante dans la sécurité alimentaire et l'augmentation de la productivité[1] des céréales est un enjeu de développement fort au Burkina Faso. Par rapport à d'autres régions du monde, les rendements moyens en céréales sont faibles. Cette situation s'explique

1. Nous utilisons dans cet article indifféremment les termes de productivité et de rendements, la productivité renvoyant à la productivité de la terre et étant mesurée par la production agricole ramenée à la surface.

Figure 1. **Évolution de la productivité des céréales au Burkina Faso (kg/ha), données du ministère de l'Agriculture du Burkina Faso**



Source : les auteurs.

principalement par un faible niveau de recours aux engrais chimiques (Le Cotty *et al.*, 2018) et par l'existence de sols dégradés au sein desquels nous assistons à des pertes de nutriments sans fertilisation – organique comme minérale – suffisante (Sawadogo *et al.*, 2008). Les rendements moyens en céréales ont cependant sensiblement augmenté au cours des dernières années, comme nous pouvons le voir sur la *figure 1*. Alors qu'ils s'établissaient au début des années 2000 autour de 800 kg/ha, ils atteignent aujourd'hui plus de 1 000 kg/ha.

Les céréales sont des cultures pluviales : le niveau de leur production est donc dépendant des pluies, ce qui explique que les rendements réalisés varient fortement d'une année à une autre. Par ailleurs, ces rendements moyens cachent d'importantes variations d'une culture à une autre, d'une région à une autre et d'une exploitation à une autre.

Les rendements moyens nationaux sont d'environ 1 200 kg/ha pour le maïs, 900 kg/ha pour le sorgho et 800 kg/ha pour le mil. Le sorgho et le mil sont deux céréales traditionnelles, qui sont en général produites pour être autoconsommées par les ménages, dont le rendement est très sensible à la pluviométrie et pour lesquelles la principale stratégie d'intensification est l'utilisation de main-d'œuvre plutôt que l'application d'engrais chimique. Le maïs quant à lui est une céréale qui peut être produite pour être autoconsommée par les ménages mais qui est également de plus en plus vendue sur les marchés domestiques et dont la production mobilise l'application d'engrais chimique.

Les régions les plus au nord, situées en zone sahélienne, présentent les plus bas cumuls pluviométriques et enregistrent des rendements de céréales moyens de 600 kg/ha, alors que les régions situées au sud-ouest du pays, situées en zone soudanienne, bénéficient de cumuls pluviométriques plus avantageux et obtiennent des rendements moyens de céréales de l'ordre de 1 500 kg/ha.

Enfin, les rendements varient d'une exploitation a une autre, en fonction notamment des caractéristiques des ménages, des systèmes de production agricole choisis, des niveaux d'intensification en engrais chimiques et organiques et de la qualité des sols.

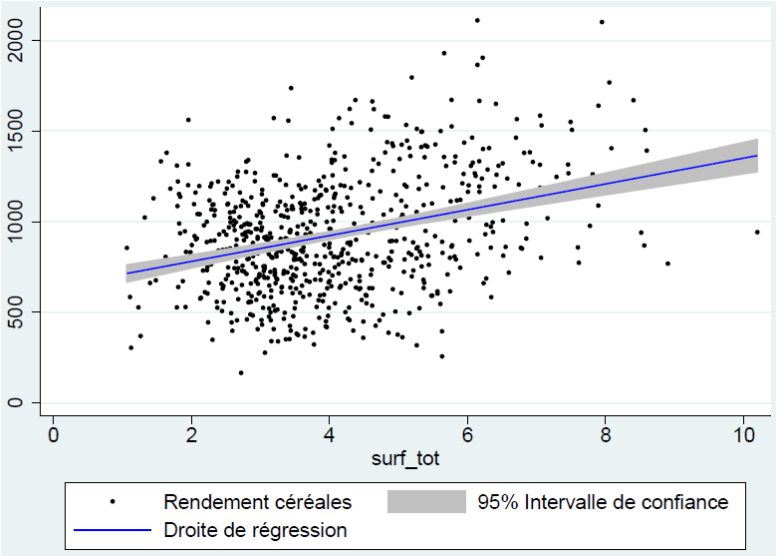
Différents facteurs ont concouru aux gains de rendement observés au cours des deux dernières décennies, et notamment l'augmentation tendancielle des cumuls pluviométriques annuels, la large diffusion de la traction animale, le développement des marchés du maïs et le développement, bien que timide, de l'utilisation de l'engrais chimique.

2. Relation positive entre taille des exploitations et productivité des céréales

Il apparaît au Burkina Faso que la productivité des céréales est d'autant plus élevée que la surface des exploitations est grande. Cette relation positive est représentée à la *figure 2*. Chaque point correspond à une observation de la taille moyenne des exploitations et du rendement moyen des céréales par province et par année. La productivité est exprimée en kilogrammes par hectare et les surfaces sont exprimées en hectares. Le Burkina Faso compte 45 provinces. Il y a 45 provinces et 18 années considérées dans notre analyse. À partir du nuage de points de toutes les observations, nous traçons une droite de régression dont la pente est significativement positive.

Cette relation positive entre la taille moyenne des exploitations et les rendements moyens observés se vérifie également pour la production de maïs. La *figure 7* (*cf. annexe*) présente une pente positive. Cette relation positive se vérifie pour toutes les années étudiées entre 1995 et 2012 et semble même s'accentuer sur la période. La *figure 8* (*cf. annexe*) montre en effet que la pente de la droite de régression est de plus en plus marquée au fil du temps.

Figure 2. **Relation entre productivité des céréales et surface totale au Burkina Faso** (moyennes par province et par an)



Source : les auteurs.

Tout semble donc indiquer que, en moyenne provinciale, les plus grandes exploitations sont plus productives au Burkina Faso. Cela va à l'encontre du fait stylisé, souvent confirmé empiriquement, selon lequel les petites exploitations sont plus productives, estampillé dans la littérature économique comme la « relation inverse entre productivité et taille » (Feder, 1985). Des études empiriques anciennes mettent en évidence cette relation négative dans de nombreux pays en développement (Bardhan, 1973 ; Berry *et al.*, 1979) sans toutefois proposer de modèle théorique à même d'expliquer cette relation, notamment sous les hypothèses classiques de fonction de production agricole à rendements constants (pas d'effet direct de la taille sur le rendement) (Berry *et al.,* 1979) et de fonctionnement parfait des marchés (Bhalla et Roy, 1988). Les modèles vont donc s'employer à expliquer l'existence d'une relation négative en relâchant les hypothèses classiques. Les deux principales raisons avancées dans la littérature pour expliquer cette relation négative sont la qualité des sols et les défaillances de marché des facteurs de production (travail, terre, capital) dans les pays en développement (Barrett *et al.*, 2010).

L'argument lié à la qualité des sols énonce que dans l'histoire de l'occupation des sols, les premières exploitations à s'installer l'ont fait sur les terres les plus fertiles (et les suivantes sur les terres moins fertiles) avant de s'agrandir par la mise en culture de terres de moins en moins fertiles. Par conséquent, les plus grandes exploitations présentent des sols plus pauvres (Benjamin, 1995). Le fait que les petites exploitations ont de meilleurs sols (Bhalla, 1988) permet d'expliquer qu'elles obtiennent de meilleurs rendements (Bhalla et Roy, 1988).

L'argument lié aux imperfections de marché concerne à la fois le marché du travail, du crédit (le capital) et celui du foncier (Heltberg, 1998). Dans les pays pauvres, il y a plus de travail familial par hectare sur les petites exploitations parce qu'il n'y a pas de marché du travail permettant d'absorber le surplus de main-d'œuvre (Bardhan, 1973). *In fine*, la production est plus intensive en main-d'œuvre sur les petites exploitations, ce qui se traduit par de meilleurs rendements. Par ailleurs, la défaillance du marché du crédit limite l'achat d'intrants et l'investissement agricole, et donc in fine les gains de rendement (Feder, 1985). Si l'accès au crédit est limité, l'accès au capital pour investir et l'accès aux intrants sont limités également. Ainsi, plus la surface augmente, plus les rapports capital par hectare et intrants par hectare diminuent. Cette relation négative a été mise en évidence et discutée dans de nombreux pays en développement, notamment en Inde (Carter, 1984), à Madagascar (Barrett, 1996) et au Pakistan (Heltberg, 1998). En Afrique, une étude qui associe des données de ménages et de parcelles sur douze pays africains aboutit également à une corrélation négative entre la surface des exploitations et les rendements (Larson *et al.*, 2014).

Cependant, d'autres travaux ont contribué à remettre en cause l'existence d'une relation négative. Feder (1985) a proposé un cadre théorique dans lequel la taille de l'exploitation ne joue sur la productivité agricole que dans le cas où l'exploitation emploie de la main-d'œuvre salariée et où l'effectivité du travail salarié est sensible à la supervision du travail. Dans ce cas, la relation entre la taille et la productivité peut être négative ou positive en fonction du degré de sensibilité du travail à la supervision et de l'élasticité de la production à la taille (hypothèse de production à rendements constants ou non). Ainsi, si les grandes exploitations ont davantage accès au capital et en conséquence peuvent avoir recours a davantage de main-d'œuvre salariée cela ne se traduira par des rendements plus élevés que si les exploitations sont en

mesure de superviser le travail (Eswaran et Kotwal, 1986).

Sur le plan empirique, des études remettent en question la relation négative entre taille et productivité en mettant en avant une relation positive (Kevane, 1996 ; Collier et Dercon, 2014 ; Zaibet et Dunn, 1998 ; Chand *et al.*, 2011) ou bien l'absence de relation significative (Benjamin, 1995) ou encore en mettant en avant l'existence d'une relation en U (Carter et Wiebe, 1990). Au Kenya par exemple, du fait de l'imperfection des marchés du travail et du crédit, il a été montré que les petites exploitations étaient très intensives en main-d'œuvre, mais qu'à l'autre bout du spectre, les grandes exploitations avaient plus de facilités pour accéder au crédit *ex ante*, ce qui leur permettait également d'obtenir des niveaux élevés de productivité. Une étude conduite à Java montre que la relation négative entre la taille et la productivité ne tient plus lorsque l'on prend en compte les imperfections du marché du travail et la qualité de la terre (Benjamin, 1995). Une étude menée au Soudan aboutit ainsi à une relation positive entre la surface des exploitations et les rendements (Kevane, 1996) et met en avant les contraintes de liquidité comme éléments explicatifs. Selon Kevane (1996), les exploitations les plus riches – les plus grandes – ont moins de contraintes de liquidité et peuvent donc davantage intensifier leur production agricole. Pour Collier et Dercon (2014), des économies d'échelle sont possibles et expliqueraient que dans certains contextes nous ayons une relation positive entre la taille des exploitations et la productivité agricole. Ces économies d'échelle sont réalisables *via* l'adoption d'innovations technologiques particulières : l'argument présenté est que les grandes exploitations sont dirigées par des personnes plus éduquées et plus susceptibles d'adopter les innovations. Les effets de l'innovation sont insensibles à la taille (par exemple, il n'y a aucune raison de penser que l'engrais soit plus rentable sur de grandes exploitations que sur de petites exploitations), mais son adoption ne l'est pas, et se fait plus rapidement dans le cas des grandes exploitations (Collier et Dercon, 2014). Des économies d'échelle peuvent également être réalisées dans le domaine du stockage, de la transformation, de la commercialisation des produits agricoles et pourraient expliquer une relation positive entre la taille des exploitations et la productivité agricole (Collier et Dercon, 2014). Cet argument semble corroborer une étude menée en Tunisie dans laquelle les plus grandes exploitations sont davantage orientées vers la commercialisation et présentent de meilleurs rendements (Zaibet et Dunn, 1998). Ces arguments empiriques semblent indiquer que la relation inverse entre productivité et taille pourrait n'être valable que pour une forme d'agriculture traditionnelle mais pas pour les formes d'agriculture commerciale qui financent les facteurs de production fixes et variables (investissement en capital, rémunération de main-d'œuvre et achat d'engrais) (Chand *et al.*, 2011 ; Collier et Dercon, 2014).

3. L'accès à l'engrais *via* la production de coton comme facteur explicatif potentiel

Au Burkina Faso, la grande majorité des exploitations agricoles correspond à des formes d'agriculture traditionnelle où la main-d'œuvre est essentiellement familiale. Par ailleurs, les arguments sur la qualité des sols et sur la défaillance des marchés du crédit et du travail semblent plausibles. Ces éléments devraient nous orienter vers une situation dans laquelle la relation entre la taille et le rendement serait négative. L'explication d'une relation positive est donc ailleurs. Notre hypothèse est qu'au Burkina Faso, produire du coton permet de lever la contrainte de crédit et supprime la relation négative attendue entre taille des exploitations et rendement. La production de coton au Burkina Faso

est encadrée par des sociétés cotonnières qui ont intégré verticalement certaines fonctions et se chargent notamment de la distribution d'engrais chimique à crédit aux producteurs. L'engrais est avancé en début de saison culturale. Il est ensuite remboursé aux sociétés cotonnières en fin de saison *via* une déduction de son coût sur le prix d'achat du coton aux producteurs. L'engrais distribué par ce mécanisme bénéficie à la fois à la production de coton et à celle de maïs. Historiquement, seule la production de coton bénéficiait de ce système de préfinancement de l'engrais chimique. Cependant, l'engrais était détourné par les producteurs vers la production de maïs, ce qui a engendré des situations de défaut de paiement et a été considéré comme une des raisons de l'inefficacité de la filière coton (Dowd-Uribe, 2014). Pour pallier cette situation, les sociétés cotonnières ont introduit un mécanisme de distribution rationnée de l'engrais pour les productions de coton et de maïs qui dépend des surfaces déclarées en coton. Les quantités d'engrais attribuées sont au maximum de trois sacs de NPK[2] pour le coton par ha de coton déclaré et de un sac de NPK pour le maïs par hectare de coton déclaré. Ce qui revient à dire qu'il y a un plafonnement de l'engrais obtenu pour le maïs a un tiers de l'engrais obtenu pour le coton.

Pour se protéger contre le risque de défaut de paiement, des enquêtes terrain sont régulièrement menées pour s'assurer de l'utilisation des engrais obtenus. Le coût des engrais coton et maïs est ensuite déduit de la vente du coton.

La contrainte de crédit, ajoutée à la faiblesse des liquidités financières des ménages agricoles au moment de l'installation des cultures fait que les exploitations sont limitées dans leurs achats d'intrants agricoles et dans leurs décisions d'investissement agricole. Les conséquences sont qu'une augmentation de surface s'accompagne d'une diminution du ratio intrants par hectare et du ratio capital par hectare, et que les petites exploitations sont plus productives que les grandes. Les liquidités financières des ménages agricoles sont limitées au Burkina Faso, surtout à l'installation des cultures. Celle-ci coïncide avec la période de soudure en Afrique subsaharienne, marquée par l'affaiblissement, voire l'épuisement, des stocks de céréales donc des possibilités d'accès aux liquidités financières pour les ménages agricoles. L'accès au crédit rural est par ailleurs très limité au Burkina Faso. La frilosité des institutions financières à se positionner en milieu rural tient aux nombreux risques qui pèsent sur l'activité agricole et à la faiblesse des garanties financières dont disposent les ménages agricoles. L'accès au crédit est cependant plus développé dans la zone soudanienne au travers du crédit engrais fourni par les sociétés cotonnières pour la production de coton et de maïs. L'engrais est distribué à crédit pour le coton (trois sacs de NPK par hectare de coton déclaré) et pour le maïs (un sac de NPK par hectare de coton déclaré). Le nombre de sacs d'engrais obtenus pour le maïs est plafonné (*supra*) à un tiers des sacs obtenus pour le coton. Ce qui revient à dire que la surface de maïs financée par le crédit intrant correspond au maximum à un tiers de la surface de coton financée[3].

Plus la surface cultivée en coton est grande, plus l'accès à l'engrais à crédit pour la production de maïs est grand et permet de lever la contrainte de liquidité. La quantité d'engrais fournie à crédit par

2. Engrais minéral composé d'éléments d'Azote, de Potassium et de Phosphate.

3. À titre d'illustration numérique, un producteur déclarant 3 hectares de coton recevra 12 sacs de NPK : 9 sacs pour le coton – qu'il appliquera sur ses 3 ha de coton – ainsi que 3 sacs pour le maïs, qu'il appliquera sur 1 ha de maïs.

les sociétés cotonnières dépend directement de la surface cultivée en coton.

L'idée principale défendue dans cet article est que produire du coton au Burkina Faso permet aux producteurs agricoles de lever les contraintes de liquidité et de crédit. Ces contraintes sont d'autant plus « levées » que les surfaces déclarées en coton sont importantes.

Le reste de l'article est organisé comme suit. La deuxième partie présente un modèle d'exploitation agricole adapté de Feder (1985) pour tenir compte de la complémentarité des productions de coton et de maïs au Burkina Faso. Le modèle estime la demande d'engrais du producteur agricole et intègre deux fonctions de production liées, pour le maïs et pour le coton. Le modèle aboutit à une relation de causalité entre la surface totale et le rendement du maïs. La troisième partie teste la validité empirique d'une telle relation, à partir de la combinaison de bases de données sur les prix, sur les cumuls pluviométriques et sur les caractéristiques des ménages et des exploitations agricoles au Burkina Faso. Les données correspondantes à la période 1995 à 2012 couvrent l'ensemble du territoire du Burkina Faso (45 provinces) et sont traitées en panel par la méthode des moments généralisés.

Un modèle de production agricole avec rationnement d'engrais

1. Le maïs et le coton, deux productions liées

Chez Feder, le travail salarié est le principal facteur de production, mais dans notre cas, la quantité d'engrais utilisée est le principal facteur de production de maïs, dont nous cherchons à expliquer l'utilisation. Dans notre analyse, nous considérons deux productions, le maïs et le coton. Pour simplifier, nous supposons que la production de ces cultures est séparable des autres du point de vue technologique.

Nous avons donc deux fonctions de production $Y^m = F(X^m, S^m)$ et $Y^c = G(X^c, S^c)$ pour le maïs et le coton, respectivement, où les X_i sont les quantités d'engrais utilisées pour la culture i, les S_i sont les surfaces cultivées en culture i.

Comme dans Feder (1985), nous supposons que la technologie est à rendement constant : la taille de l'exploitation agricole en tant que telle n'a pas d'effet sur les rendements. À même dose d'engrais par hectare, une exploitation d'un hectare a les mêmes rendements qu'une exploitation de deux hectares. Si les rendements augmentent entre une exploitation d'un et de deux hectares, c'est donc que l'exploitation de deux hectares met plus d'engrais par hectare. Cela permet de ne pas présupposer que, par elle-même, la taille joue sur le rendement. Une telle technologie à rendements constants implique que les fonctions de production peuvent être ramenées à des fonctions de production à l'hectare, production

$$y^m = \frac{Y^m}{S^m} = f(x^m)$$

et

$$y^c = \frac{Y^c}{S^c} = g(x^c)\,,$$

où les x_i sont les doses d'engrais par hectare.

La culture du maïs peut utiliser de l'engrais acheté par les producteurs sur le marché. Cependant, pour simplifier, nous considérons que l'ensemble de l'engrais pour la culture du maïs $x^m S^m$ est fourni par les sociétés cotonnières, et seulement aux producteurs de maïs qui produisent aussi du coton. La quantité fournie par les sociétés cotonnières pour le maïs est plafonnée en fonction de la surface en coton, $x^m S^m \leq \alpha S^c$. Le coton requiert également de l'engrais $x^c S^c$ fourni par les sociétés cotonnières en proportion de la surface cultivée en coton, $x^c \leq \gamma$. En pratique, le seul cas

pertinent dans le contexte étudié est celui où les producteurs utilisent tout l'engrais disponible et la fonction de production du coton ne dépend alors plus que de la surface en coton puisque le producteur agricole ne choisit pas le degré d'intensification du coton : $y^c S^c = g(\gamma)S^c$. Au Burkina Faso, en pratique, $\alpha = 1$ et $\gamma = 3$ lorsque les quantités d'engrais sont exprimées en nombre de sacs de 50 kg de NPK et les surfaces exprimées en hectares. Enfin, la surface cultivée en coton est elle même limitée par négociation au sein des groupements de producteurs de coton qui contractent le crédit. L'enjeu de cette limitation est d'éviter de cultiver de trop grandes surfaces de coton en obtenant un crédit trop important par rapport à la capacité des ménages à le cultiver suffisamment bien pour rembourser le crédit. Mais il s'agit d'une contrainte floue et nous n'en tenons pas compte dans ce modèle. Enfin, nous supposons que la production de coton n'est possible qu'à partir d'une certaine superficie. Les plus petites exploitations ne font que du maïs pour nourrir leur famille sans prendre le risque de produire une culture de rente et sans acheter d'engrais. À partir d'une certaine taille, elles commencent à semer du coton parallèlement à leur maïs. Cette hypothèse correspond à une réalité empirique (*figure 4*).

2. Le problème général

Le programme du producteur s'écrit :

$$\max_{x^m, x^c, S^m, S^c} \pi = p^c y^c S^c + p^m y^m S^m - w(S^c x^c + S^m x^m) \quad (1)$$

$$S^c + S^m \leq S$$

$$(S^m - \underline{S}^m)S^c \geq 0$$

$$x^m S^m \leq \alpha S^c$$

$$x^c S^c \leq \gamma S^c$$

$$y^m = f(x^m)$$

$$y^c = g(x^c)$$

La variable w est le prix de marché de l'engrais supposé identique au prix de fourniture de l'engrais par les sociétés cotonnières, S est la surface cultivable du ménage.

La deuxième contrainte traduit le passage de l'agriculture de subsistance à la coexistence coton-maïs. Le seuil $\underline{S}^m$ est la surface de maïs minimale pour commencer à faire du coton. Si $S^m \geq \underline{S}^m$ alors S_c peut être strictement positif, mais si $S^m < \underline{S}^m$, on a nécessairement $S^c = 0$.

Les troisième et quatrième contraintes sont les contraintes sur les engrais fournis par la Sofitex.

Le lagrangien s'écrit :

$$L(x^m, x^c, S^m, S^c) = p^c y^c S^c + p^m y^m S^m - w(S^c x^c + S^m x^m) + \lambda(S - S^c - S^m) + \eta(S^m - \underline{S}^m)S^c + \mu(\alpha S^c - x^m S^m) + \rho(\gamma S^c - x^c S^c) \quad (2)$$

Avec

$$\lambda \geq 0 \; ; \; (S - S^c - S^m) \geq 0 \; ; \; \lambda\,(S - S^c - S^m) = 0$$

$$\eta \geq 0 \; ; \; (S^m - \underline{S}^m)S^c \geq 0 \; ; \; \eta(S^m - \underline{S}^m)S^c = 0$$

$$\mu \geq 0 \; ; \; \alpha S^c - x^m S^m \geq 0 \; ; \; \mu(\alpha S^c - x^m S^m) = 0$$

$$\rho \geq 0 \; ; \; \gamma S^c - x^c S^c \geq 0 \; ; \; \rho(\gamma S^c - x^c S^c) = 0$$

La dérivation de ce programme, respectivement par rapport à x^m, x^c, S^m et S^c, donne les conditions de premier ordre :

$$p^m S^m f' - wS^m - \mu S^m = 0 \quad (3)$$

$$p^c S^c g' - wS^c - \rho S^c = 0 \quad (4)$$

$$p^m y^m - wx^m - \lambda + \eta S^c - \mu x^m = 0 \quad (5)$$

$$p^c y^c - wx^c - \lambda + \eta(S^m - \underline{S}^m) + \mu\alpha + \rho(\gamma - x^c) = 0 \quad (6)$$

Nous étudions le cas le plus général au Burkina Faso où toute la surface est utilisée, $\lambda > 0$ et $S^m = S - S^c$ et la quantité d'engrais fournie par la Sofitex est limitante pour le coton $\rho > 0$; $\gamma S^c - S^c x^c = 0$ et pour le maïs, $\mu > 0$ et $x^m = \alpha \frac{S^c}{S^m}$. Le problème devient :

$$p^m f' - w - \mu = 0 \quad (7)$$

$$(p^c g' - w - \rho)S^c = 0 \quad (8)$$

$$p^m y^m - w\alpha \frac{S^c}{S^m} - \lambda + \eta S^c - \mu\alpha \frac{S^c}{S^m} = 0 \quad (9)$$

$$p^c y^c - wx^c - \lambda + \eta(S^m - \underline{S}^m) + \mu\alpha = 0 \quad (10)$$

La résolution dépend essentiellement de la contrainte de subsistance.

3. La contrainte de subsistance est non contraignante

Si la contrainte de subsistance n'est pas contraignante, cela signifie que $S^m > S^m$, $S^c > 0$ et $\eta = 0$. La différence (9) – (10), en substituant S^c par γ, donne :

$$p^m y^m - p^c y^c - w(\alpha \frac{S^c}{S^m} - \gamma) - \mu\alpha(1 + \frac{S^c}{S^m}) = 0 \quad (11)$$

On introduit la valeur de μ donnée par l'équation (7).

$$p^m y^m - p^c y^c - w(\alpha \frac{S^c}{S^m} - \gamma) - (p^m f' - w)\alpha(1 + \frac{S^c}{S^m}) = 0 \quad (12)$$

Soit :

$$p^m y^m - p^c y^c + w(\alpha + \gamma) - p^m f' \alpha(1 + \frac{S^c}{S^m}) = 0 \quad (13)$$

Nous cherchons à exprimer la part de surface en coton S^c/S en utilisant $S^m = S - S^c$:

$$[p^m y^m - p^c y^c + w(\alpha + \gamma) - p^m f'\alpha](S - S^c) = p^m f'\alpha S^c \quad (14)$$

Qui peut s'écrire :

$$\frac{Sc}{S} = \frac{p^m y^m - p^c y^c + w(\alpha+\gamma) - p^m f'\alpha}{p^m y^m - p^c y^c + w(\alpha+\gamma)} \quad (15)$$

Ceci définit une part de surface optimale en coton qui ne dépend pas de S. En effet, appelons $\theta = S^c/S$ la part de surface en coton, on a alors

$$x^m = \frac{\alpha S^c}{S - S^c} = \alpha\theta/(1-\theta),$$

donc la fonction de production peut se redéfinir en fonction de θ : $y^m = f(x^m) = h(\theta)$. On se souvient par ailleurs que $y^c = g(\gamma)$. L'optimum ci-dessus se réécrit :

$$\theta^* = 1 - \frac{\alpha p^m h'(\theta^*)}{p^m h(\theta^*) - p^c g(\gamma) + w(\alpha+\gamma)} \quad (16)$$

La part de surface en coton ne dépend pas de S, donc l'engrais utilisé sur le coton ne dépend pas de S, donc le rendement du maïs ne dépend pas de S.

Si les contraintes sur les engrais ne sont pas saturées, il est clair que l'accroissement de la surface totale n'augmente pas non plus le rendement du maïs puisqu'il était déjà à l'optimum. En revanche, dans le cas où la contrainte de sécurité alimentaire est contraignante, $\eta > 0$ et $S^m = S^m$ apporte une différence.

4. La contrainte de subsistance s'exerce mais la production de coton est possible

Ce cas se définit par $\eta > 0$; $S^m = S^m$; $S^c > 0$. Lorsque le ménage dispose d'une surface suffisante pour nourrir sa famille, il consacre le reste de sa surface à la culture du coton. C'est le cas le plus général empiriquement (*cf. figure 4*). Lorsque la surface totale dépasse 3 ha, la pente de la courbe est proche de 1, ce qui signifie que presque tout accroissement de surface au-delà de 3 ha est consacré au coton.

Dans ce cas, θ augmente avec S puisque $\theta = S^c/S = (S - S^m)/S = 1 - S^m/S$.

Comme $x^m = \alpha\theta/(1-\theta)$, également croissant en θ, $y^m = f(x^m)$ est donc croissant en S.

Même si la surface de maïs n'augmente pas, la production de maïs augmente car la surface en maïs reçoit maintenant de l'engrais.

5. La contrainte de subsistance empêche la production de coton

Dans cette situation, où la surface cultivée est faible, le producteur ne produit que du maïs sans intrant. Nous avons alors $\eta > 0$; $S^c = 0$; $S^m < S^m$. Le rendement du maïs est

constant et indépendant de la surface cultivée. Cette situation se produit jusqu'à ce que la surface cultivée atteigne S^m, à partir de laquelle le producteur commence à faire du coton.

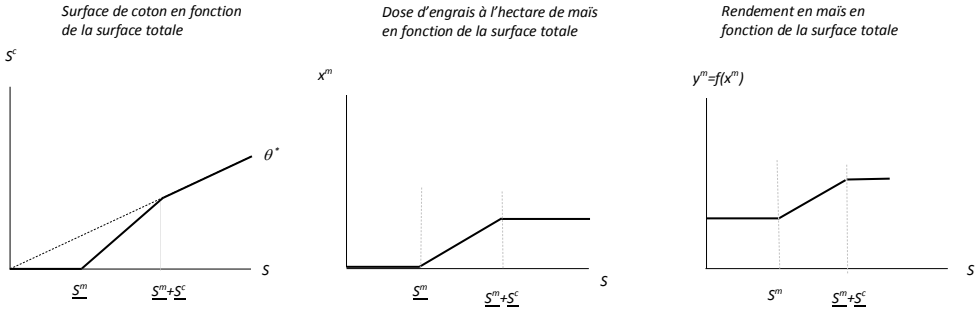
6. Illustration de la solution globale

La *figure 3* représente l'effet théorique d'un accroissement de la surface cultivée sur les choix du producteur en matière de surface en coton, de dose d'engrais sur le maïs, et donc de rendement.

Dans la partie gauche des trois schémas correspondant à ces choix, lorsque $S < S^m$, la surface totale est trop faible pour que le ménage puisse produire du coton et toute sa surface est consacrée au maïs. Il n'utilise pas d'engrais et le rendement du maïs ne varie pas avec la surface totale.

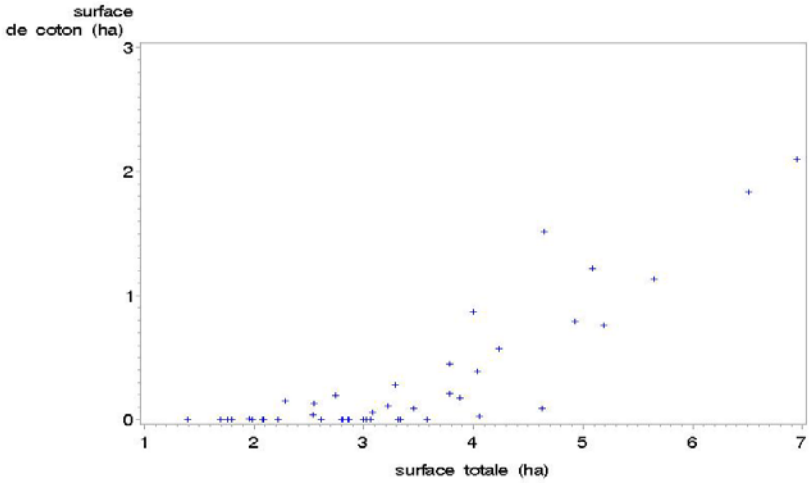
Dans la partie intermédiaire où $S^m < S < S^m + S^c$, le ménage consacre toute sa surface supplémentaire à la culture du coton. La pente de la droite sur ce segment est égale à 1, et S^c est la surface de coton minimale à partir de laquelle le rapport des surfaces devient optimal (et la surface de maïs recommence à augmenter). L'idée est que les ménages concernés rattrapent

Figure 3. **Solution globale**



Source : les auteurs.

Figure 4. **Observations de la surface de coton en fonction de la surface totale, année 2010**



Source : les auteurs.

l'optimum économique le plus « vite » possible, or cet optimum se caractérise dans notre modèle par une plus grande proportion de coton (θ^*). L'utilisation d'engrais pour le maïs augmente avec S car S^c augmente plus vite que S en valeur relative (on rappelle que $x^m = \frac{\alpha S^c}{S - S^c}$). Le rendement du maïs augmente avec x^m.

Dans la partie de droite, $S > S^m + S^c$, le ménage a maintenant « retrouvé » sa proportion optimale de coton/maïs et les deux surfaces augmentent en proportion fixe. La dose d'engrais du maïs devient constante et le rendement du maïs aussi.

7. Effet attendu

En théorie, l'effet attendu de la surface cultivée sur la productivité du maïs devrait être nul pour les petites surfaces, positif pour les moyennes surfaces, et nul pour les surfaces plus élevées. Nous constatons sur la *figure 4* que ce dernier cas n'a apparemment pas une grande importance empirique, mais si c'était le cas, en linéarisant l'effet de la surface sur la productivité, l'effet attendu moyen sur l'ensemble de la population serait positif.

Il est possible de décomposer cet effet attendu en sous-effets qui nous aideront à donner du crédit à notre thèse. En particulier, il est attendu que la productivité du maïs soit plus élevée lorsque le producteur produit aussi du coton, et lorsque la surface de coton augmente, ce qui en théorie va avec l'accroissement de la surface totale.

Estimation empirique

Nous cherchons à tester l'effet de la surface totale sur la productivité des céréales, et en particulier du maïs, dans les systèmes de production agricole du Burkina Faso. Sur la période 1995-2012, nous avons mobilisé des données ménages, des données de pluviométrie et des données de prix.

La plupart des articles sur la relation entre taille des exploitations agricoles et productivité se situent au niveau de l'exploitation agricole, c'est-à-dire toutes cultures confondues. Quelques articles toutefois se situent au niveau des parcelles et portent donc de manière spécifique sur certaines cultures, comme le riz à Madagascar (Barrett, 1996) ou bien le maïs en Zambie (Kimhi, 2006). Dans cet article, nous analysons l'effet de la surface totale sur la productivité globale des céréales ainsi que sur la productivité partielle du maïs, du mil et du sorgho.

1. Estimation d'un modèle de panel

Des observations au niveau provincial

Les données ménages portent sur des décisions individuelles, et sont disponibles pour environ 4 500 ménages (une observation par ménage et par an). Les données de pluviométrie et les données de prix des produits agricoles sont quant à elles disponibles au niveau provincial, sur une base de 45 provinces (une observation par an et par province pour la pluviométrie, une observation par mois et par province pour les prix). Nous avons procédé à une agrégation des données ménages au niveau provincial pour mettre en correspondance ces données aux autres types de données. Chaque variable individuelle (surface, rendement notamment mais également les autres types de données) est ramenée à sa moyenne provinciale. L'enquête ménage réalisée chaque année s'appuie sur un design de randomisation à deux étapes. Dans un premier temps, les villages sont choisis aléatoirement par province, leur nombre dépendant de la population de chaque province. Dans un second temps, les ménages sont choisis aléatoirement au sein des villages. Cette randomisation en deux temps fait que les ménages enquêtés sont représentatifs des ménages agricoles au niveau de la province et que nous pouvons avoir recours à des moyennes provinciales pour analyser la diversité des décisions agricoles.

Il est certain que l'agrégation des données ménages au niveau provincial correspond à une perte d'information dans la mesure où l'agrégation « écrase » la variabilité des comportements des ménages au sein des provinces et privilégie une analyse de la variabilité des comportements individuels d'une province à une autre. Nous obtenons ainsi un panel dans lequel les variables comme les prix et la pluviométrie changent avec la même fréquence que la variable endogène. Si ce n'était pas le cas, les estimateurs pourraient être biaisés, du fait de la stabilité de certaines variables exogènes. L'échantillonnage réalisé par le ministère de l'Agriculture du Burkina Faso nous assure de la représentativité des données individuelles collectées au niveau provincial et nous permet donc de transposer en toute confiance les mécanismes individuels décrits dans le modèle théorique à l'échelle provinciale. D'autres papiers modélisent des décisions individuelles à partir de données agrégées, obtenues à partir d'un échantillon large et choisi de manière aléatoire (Balestra et Nerlove, 1966).

La surface moyenne d'un ménage à l'échelle d'une province est probablement moins exogène que la surface individuelle d'un ménage dans une province. En effet, elle peut résulter de trajectoires similaires de nombreux producteurs qui dépendent notamment du rendement espéré dans la province. Par exemple, les conditions pédoclimatiques favorables aux hauts rendements risquent de favoriser l'accroissement de la population locale et donc de réduire la surface disponible par ménage. Les provinces plus urbaines risquent d'exposer les producteurs à une demande plus forte en céréales, et donc de stimuler les rendements, mais aussi les accroissements de surface s'il reste des terres disponibles. La spécialisation des activités, par exemple liée au climat ou à l'existence de microfinance, peut aussi impacter la surface cultivée. Ces éléments constituent de l'hétérogénéité inobservée corrélée à la surface cultivée conduisant à remettre en cause l'hypothèse d'indépendance conditionnelle des aléas, nécessaire en cas de régression linéaire.

L'exploitation des données de panel permet de corriger en partie ce problème d'hétérogénéité inobservée corrélée à la surface cultivée. Un panel à effet fixe permettrait de corriger ce problème si l'hétérogénéité inobservée était constante, mais pas si c'est une trajectoire liée à l'urbanisation ou à toute autre dynamique. Pour cela, il nous faut estimer un panel dynamique corrigeant, autant que possible, l'effet que pourrait avoir le rendement passé sur la surface cultivée.

Un modèle de panel avec effet retard

L'estimation d'un modèle statique n'est pas très performante parce que les effets géographiques dominent trop nettement les effets temporels. Si nous comparons les provinces entre elles, la relation entre le prix et la production est négative, car les régions les plus productives engendrent des prix en moyenne plus faibles. Afin que le prix soit une variable exogène de la production, nous utilisons le prix observé avant la décision de produire, comme nous comparons la productivité après une année de faible prix et la productivité de cette région après une année de prix élevé. Nous nous attendons alors à une relation positive entre le prix et la productivité.

L'équation (17) qui suit est la version linéarisée de notre modèle théorique. Dans le modèle théorique, le rendement du maïs dépend : de la surface totale, de la surface minimale avant de faire du coton, S^m, du prix du coton, du prix du maïs, et du prix des engrais. Nous ne disposons pas de données sur le prix des engrais, mais les prix sont uniformes et varient peu dans le temps. Nous ne disposons pas non plus de données sur le prix du coton, ce qui est plus problématique parce qu'il varie

d'une année à l'autre, et c'est une source d'imprécision dans notre estimation. Cela étant dit, le prix du coton joue sur le rendement du maïs pour les surfaces les plus grandes (partie droite de la *figure 3*, cf. équation 16), qui n'est empiriquement pas prépondérante. Par ailleurs, la contrainte de surface minimale avant de faire du coton est remplacée par une dummy valant 1 si le ménage produit du coton, et le cumul pluviométrique est une variable implicite de la fonction de production $y^m = f(x^m)$.

$$y_{ijt} = a_0 + a_1 S_{it} + a_2 \mathrm{I}_{coton,it} + a_3 \mathrm{PLUIE}_{it} + a_4 p_{jt-1} + Z_{it} b + \mu_i + \upsilon_t + \varepsilon_{ijt} \quad (17)$$

où Z_{it} est un vecteur de variables individuelles exogènes et y_{ijt} est la productivité moyenne par ha des céréales de type j dans la province i pour l'année t. La variable S_{it} est la surface totale disponible pour l'agriculteur moyen de la province i pour l'année t.

De par les problèmes d'endogénéité potentiels entre les variables explicatives et les rendements, nous introduisons un effet retard dans le modèle que nous estimons comme suit :

$$y_{ijt} = b_0 + b_1 y_{it-1} + b_2 S_{it} + b_3 \mathrm{I}_{coton,it} + b_4 \mathrm{PLUIE}_{it} + b_5 p_{jt-1} + Z_{it}\gamma + \chi_{ijt} \quad (18)$$

La prise en compte d'un effet retard, par l'introduction d'une variable de rendement décalée, permet de corriger les problèmes d'endogénéité pouvant provenir d'un ajustement progressif de la surface cultivée aux rendements espérés. Par exemple, le fait qu'une province ait une productivité élevée la rend plus attractive, ce qui peut aboutir à accroître la pression foncière et réduire la surface disponible par actif agricole. Dans ce cas, la qualité des sols pourrait expliquer à la fois les surfaces et les rendements et serait alors une source d'hétérogénéité inobservée causant un biais dans le coefficient a_1. En principe, les effets fixes d'un panel permettent de capturer cette hétérogénéité et corriger le biais, seulement si elle est constante, or ce n'est vraisemblablement pas le cas ici. Non seulement la qualité du sol n'est pas constante en fonction des trajectoires locales, mais d'autres facteurs affectent à la fois les surfaces et les rendements d'une manière non constante (spécialisation, urbanisation, etc.). Pour cette raison, il est préférable d'estimer un panel avec variable retardée, destiné à capturer les effets de l'histoire passée de la région qui expliquent les relations entre surfaces et rendement autres que la relation que nous cherchons à mettre en évidence.

Nous utilisons l'estimateur de la méthode des Moments Généralises (GMM) de Arellano et Bond (1991). Cette méthode est adaptée à la prise en compte de cet effet retard dans une structure de panel. Elle permet d'instrumenter : la variable surface par des différences interannuelles passées, les valeurs en niveau passées de cette même variable, ainsi que de la pluviométrie exogène avec certitude.

Après estimation, il s'avère que le rendement est très peu déterminé par le rendement passé (les données montrent un comportement instable des rendements, très déterminés par les pluies et par les prix, eux-mêmes très volatils au Burkina). Mais l'enjeu d'utiliser la méthode des GMM, en cas d'hétérogénéité inobservée non constante, demeure pour l'instrumentation de la surface.

Présentation des variables

Les variables expliquées dans notre modèle économétrique sont le rendement du maïs, du sorgho et du mil, principales céréales produites au Burkina Faso. Les variables explicatives retenues sont : (1) le rendement provincial moyen de l'année passée des céréales ; (2) la surface totale cultivée de l'exploitation provinciale moyenne, cette surface pouvant être décomposée en surface cultivée hors coton et en surface cultivée en coton afin de déterminer si

l'effet de la surface sur le rendement est plus particulièrement lié à la production de coton (test empirique du mécanisme explicatif présent dans notre modèle théorique) ; (3) une indicatrice de l'existence du coton dans les systèmes de production provinciaux (qui prend la valeur 1 s'il y a du coton produit dans la province et 0 sinon) ; (4) le cumul pluviométrique de l'année en cours dans la province ; et (5) la moyenne provinciale des prix des céréales au cours de l'année précédente. Les variables (2) et (3) nous permettent de tester directement la validité empirique des effets théoriques attendus.

La dynamique de production passée a pu impacter le prix $P_{j,t-1}$, ce qui pourrait rendre cette variable endogène. Pour purger le coefficient associé à cette variable, b_5, des effets passés de la production sur les prix d'équilibre, on introduit la variable de rendement décalé, y_{ijt-1}, qui est censée capturer les effets de la dynamique passée.

Si $b_2 > 0$, c'est que $\frac{y'}{dS} > 0$ (principal effet attendu).

Les effets fixes provinces traduisent le fait que les rendements entre provinces ne sont pas comparables puisque des variables non observables comme la qualité des sols et la pression démographique diffèrent. L'estimation en panel dynamique ne considère pas directement ces effets fixes mais intègre cette hétérogénéité inobservée dans l'estimation des paramètres.

2. Présentation des données

L'estimation du modèle dynamique que nous venons de présenter se fait par la mobilisation de trois bases de données originales.

La première est issue de l'enquête permanente agricole menée par le ministère de l'Agriculture du Burkina Faso chaque année auprès d'un échantillon représentatif d'environ 4 500 ménages agricoles couvrant l'ensemble des 45 provinces du pays. Les données sont collectées chaque année en novembre, après les récoltes des cultures pluviales. La base de données utilisée correspond à la fusion de 18 bases de données annuelles et à la constitution de moyennes provinciales à partir des données des ménages. Le *tableau 1* présente les principales variables utilisées.

La deuxième base de données utilisée est celle des cumuls pluviométriques annuels

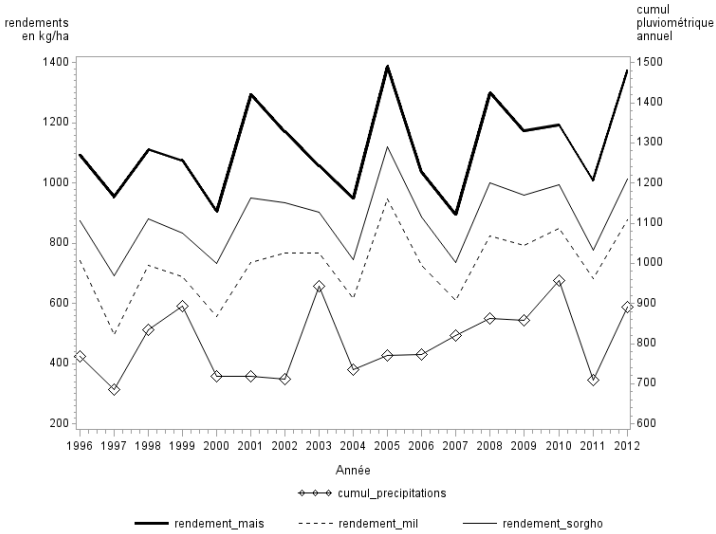
Tableau 1. **Description des exploitations agricoles étudiées** (moyennes provinciales sur la période 1995-2012)

Variable	Moyenne	Écart-Type	Min	Max
Nombre de membres du ménage	10,5	1,7	5,9	17,4
Nombre d'actifs dans le ménage	6,7	1,3	2,9	11,1
Surface en maïs (ha)	0,4	0,6	0,0	2,7
Surface en mil (ha)	1,2	0,9	0,0	5,3
Surface en sorgho (ha)	1,4	0,7	0,0	3,6
Surface en coton (ha)	0,4	0,7	0,0	3,8
Surface totale (ha)	4,1	1,5	1,1	10,2
Nombre de têtes de bétail	6,3	3,8	0,3	27,8
Nombre de charrues	1,1	0,5	0,0	2,8
Rendement de maïs (kg/ha)	1 119	435	60	2 960
Rendement de mil (kg/ha)	734	221	148	1 444
Rendement de sorgho (kg/ha)	888	244	185	1 654

Note : 62 % des ménages enquêtés produisent du coton.

Source : données du ministère de l'Agriculture du Burkina Faso.

Figure 5. **Évolution des précipitations et des rendements moyens nationaux de céréales au Burkina Faso**



Source : les auteurs.

au niveau des 45 provinces étudiées, fournis par la direction de la Météorologie. L'évolution des cumuls pluviométriques annuels depuis 1980 est présentée par la *figure* 9 en *annexe*, pour trois zones climatiques distinctes : la zone sahélienne (plus au nord), la zone soudano-sahélienne et la zone soudanienne (plus au sud). Les cumuls pluviométriques sont plus importants dans les zones situées au sud. La *figure 5* met en parallèle l'évolution des précipitations moyennes et des rendements moyens de maïs, mil et sorgho au Burkina Faso.

Nous voyons que les cumuls pluviométriques varient fortement d'une année à l'autre et que sur le temps long il pleut de plus en plus (tendance positive). Par ailleurs, les rendements sont corrélés positivement aux cumuls pluviométriques.

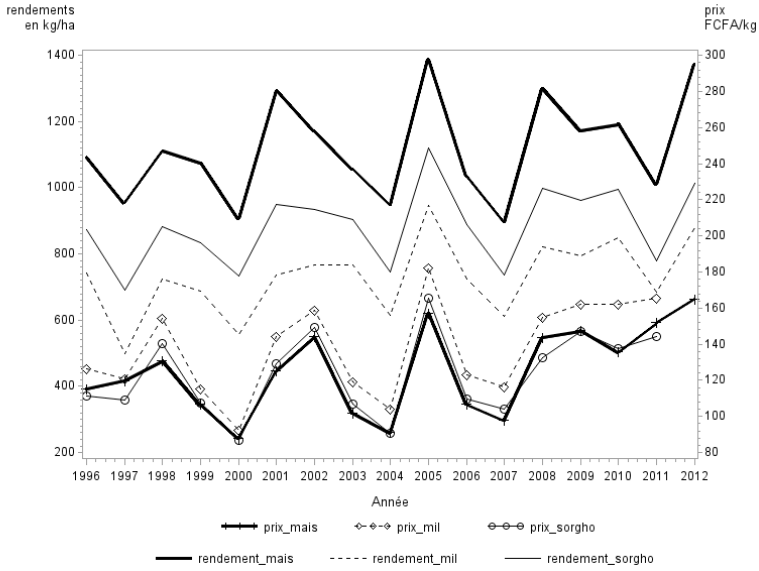
La troisième base de données utilisée est celle des prix des céréales publiés chaque mois par la société nationale de gestion du stock de Securit au niveau des 45 provinces étudiées. Les prix utilisés dans les régressions sont les moyennes annuelles non pondérées des prix relevés sur la période de janvier à juillet, c'est-à-dire avant l'installation des cultures afin d'éviter les problèmes de causalité inverse et d'endogénéité. Les céréales sont des cultures pluviales au Burkina Faso, leur saison de culture correspond à la saison des pluies et s'étend de juillet à octobre. La *figure 6* met en parallèle l'évolution des prix courants et des rendements moyens de maïs, mil et sorgho au Burkina Faso.

Les prix moyens du maïs, du mil et du sorgho suivent des évolutions comparables, ce qui indique que globalement les productions sont substituables. Les prix moyens varient fortement d'une année à l'autre. Nous voyons que les rendements sont positivement corrélés dans le temps aux prix courants, indice que des prix élevés sur la période pré-culturale (de janvier à juillet) sont des incitations pour les producteurs à intensifier leurs productions.

3. Résultats empiriques

L'estimation du modèle dynamique fournit les résultats suivants, consignés dans le *tableau 2*. Quatre spécifications sont

Figure 6. **Évolution des prix courants et des rendements moyens nationaux de céréales au Burkina Faso**



Source : les auteurs.

Tableau 2. **Estimation des effets de la taille des exploitations sur les rendements par la méthode des moments généralisés de Arrellano et Bond**

	Céréales (1)	Maïs (2)	Mil (3)	Sorgho (4)
Constante	18,16***	5,63	16,80***	10,06*
	(3,32)	(0,58)	(3,42)	(1,87)
Rendement décalé	0,00	-0,14	-0,09	-0,06
	(-0,01)	(-1,51)	(-1,47)	(-1,01)
Surface cultivée	34,24***	45,43**	22,60**	20,27*
	(3,09)	(2,46)	(2,32)	(1,92)
Existence de coton	190,97*	588,55***	144,58	205,72*
	(1,48)	(2,63)	(1,30)	(1,65)
Cumul pluviométrique	0,25***	0,02	0,28***	0,32***
	(3,32)	(0,14)	(4,08)	(4,34)
Prix du maïs	2,16	6,72**	4,88***	5,75***
	(1,19)	(2,12)	(2,94)	(3,28)
Prix du mil	12,92***	13,20***	2,50	3,04
	(4,70)	(2,82)	(1,03)	(1,14)
Prix du sorgho	-12,74***	-15,70**	-4,64	-5,43
	(-3,54)	(-2,52)	(-1,44)	(-1,55)
Nombre de provinces	38	38	38	38
Longueur des séries temporelles	16	16	16	16

*Notes : t-test entre parenthèses ; * (p < 0,1) ; ** (p < 0,05) ; ***(p < 0,01)*

Source : les auteurs.

présentées, selon que la variable expliquée est le rendement moyen des céréales (1), du maïs (2), du mil (3), ou du sorgho (4).

Les provinces comportant des données manquantes sur les prix n'ont pas été prises en compte dans l'analyse de panel dynamique par le logiciel. Nous avons choisi de ne pas remplacer les données manquantes, d'où la perte de sept provinces dans notre analyse économétrique.

Interprétation

Le rendement moyen en céréales de l'année passée n'a pas d'effet significatif sur le rendement moyen en céréales de cette année, ce qui traduit avant tout la forte variabilité des rendements observés d'une année sur l'autre.

La surface cultivée a un effet positif sur les rendements des trois céréales étudiées. En moyenne, l'augmentation d'un hectare de surface agricole cultivée se traduit par des gains de rendement de 20 kg/ha pour le sorgho, de 23 kg/ha pour le mil et de 45 kg/ha pour le maïs. Ce résultat confirme l'existence d'une relation positive entre taille des exploitations agricoles et productivité des céréales au Burkina Faso.

En plus de l'effet positif des surfaces cultivées, le fait de produire du coton augmente significativement les rendements moyens des céréales. En moyenne, pour une même surface cultivée globale, les producteurs de coton ont des rendements plus élevés d'environ 200 kg/ha pour les céréales et 600 kg/ha pour le maïs, ce qui semble donner du crédit au mécanisme suggéré dans la partie théorique du papier.

Nous trouvons un effet positif significatif du cumul pluviométrique sur les rendements moyens des céréales, du mil et du sorgho. Cela peut être expliqué par le fait que les productions de mil et de sorgho sont plus directement dépendantes de la réalisation de la pluie dans la mesure où elles ne dépendent que de la pluie (et de la main-d'œuvre qui ne varie pas considérablement d'une année à une autre) quand le maïs dépend de la pluie et de l'application d'engrais chimique. Les effets des prix du maïs, du mil et du sorgho sont à rapporter au caractère plus ou moins substituable ou complémentaire de ces céréales entre elles. Par exemple, l'effet significatif négatif du prix du sorgho sur les rendements en céréales et plus particulièrement sur les rendements en maïs semble indiquer une substitution du sorgho avec le maïs : si le prix du sorgho augmente, les producteurs vont avoir tendance à chercher de plus importants rendements de sorgho et moins de maïs (réallocation des facteurs). Cet effet de substitution ne s'applique pas pour le mil (céréale moins substituable au maïs) qui est en général fait en plus du maïs et pour laquelle on aurait plutôt une complémentarité (rendement de céréales et de maïs positivement corrélés au prix du mil).

Discussion

Comme test de robustesse, nous avons estimé trois modèles économétriques dans lesquels les rendements de chaque culture dépendent des prix de la culture en question et non des autres prix. Les résultats sont robustes à une telle spécification, à savoir que la relation entre la surface en coton et le rendement des différentes céréales reste significativement positif. Ces résultats sont présentés dans le *tableau 3* en *annexe*.

Dans notre modèle théorique, le fait de produire du coton et la surface cultivée en coton dépendent de la surface totale, qui est supposée exogène. En réalité, la production de coton dépend probablement de caractéristiques inobservées des producteurs, comme les contraintes de liquidités ou l'aptitude à produire du coton. C'est là une limite de notre estimation statistique. Néanmoins, nous pensons que la production de coton dépend beaucoup de la localisation et de la surface cultivable car les producteurs qui ont une surface cultivable suffisante dans les régions favorables à la culture de coton tendent à produire du

coton. Si la production de coton est en grande partie déterminée par la possibilité de produire du coton, nous ne pouvons toutefois pas exclure une part d'autosélection dans le choix de produire du coton, due à des facteurs inobservés.

*

* *

La productivité agricole des céréales a augmenté au Burkina Faso au cours des vingt dernières années. Le point de départ de cet article était une observation empirique selon laquelle les plus grandes exploitations sont plus productives en moyenne que les plus petites exploitations ; observation qui va à l'encontre d'un constat empirique généralement établi voulant que la productivité agricole soit plus importante pour les exploitations de petite taille. L'article analyse l'accès à l'engrais facilité via la production de coton comme facteur explicatif de la relation positive entre taille des exploitations et productivité des céréales au Burkina Faso. Le fait de produire du coton garantit aux producteurs de pouvoir accéder à l'engrais chimique sans avoir à en avancer le coût à l'installation des cultures, période de l'année où les contraintes de liquidité sont particulièrement importantes pour les producteurs agricoles (le prix de l'engrais est par la suite déduit du prix d'achat du coton). Un modèle de demande d'engrais inspiré de Feder (1985) est développé pour intégrer la spécificité des systèmes de production agricole du Burkina Faso et notamment l'interdépendance entre les productions de maïs et de coton. Le modèle établit que le rendement du maïs augmente avec la surface totale. La validité empirique de ce modèle est testée par la mobilisation de données ménages, de données de prix et de données pluviométriques sur la période 1995-2012. L'effet positif de la surface totale cultivée sur la productivité des céréales est confirmé, et il est démontré que cet effet est tiré par les surfaces cultivées en coton, ce qui confirme le mécanisme explicatif avancé. Les implications politiques d'un tel résultat sont que l'accessibilité à l'engrais est un levier important des gains de productivité réalisables et constitue donc un enjeu de développement, et de sécurité alimentaire pour le Burkina Faso. Cet accès aux engrais est aujourd'hui fortement limité compte tenu des coûts élevés de transaction et de transport mais surtout dû aux contraintes de liquidité fortes qui pèsent sur les producteurs agricoles et des imperfections du marché du crédit. Des mécanismes nouveaux de subvention du prix des engrais (smart subsidies) sont à l'étude et pourraient se traduire par une diminution du prix de l'engrais au producteur, par une augmentation conséquente du recours à l'engrais et par une amélioration de la productivité agricole des ménages. ■

RÉFÉRENCES BIBLIOGRAPHIQUES

Arellano M., Bond S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, vol. 58, n° 2, pp. 277-297.

Balestra P., Nerlove M. (1966). Pooling cross section and time series data in the estimation of a dynamic model: The demand for natural gas. *Econometrica*, vol. 34, n° 3, pp. 585-612.

Bardhan P. K. (1973). Size, productivity, and returns to scale: An analysis of farm-level data in Indian agriculture. *Journal of Political Economy*, vol. 81, n° 6, pp. 1370-1386.

Barrett C. B. (1996). On price risk and the inverse farm size-productivity relationship. *Journal of Development Economics*, vol. 51, n° 2, pp. 193-215.

Barrett C. B., Bellemare M. F., Hou J. Y. (2010). Re-considering conventional explanations of the inverse productivity-size relationship. *World Development*, vol. 38, n° 1, pp. 88-97.

Benjamin D. (1995). Can unobserved land quality explain the inverse productivity relationship? *Journal of Development Economics*, vol. 46, n° 1, pp. 51-84.

Berry R. A., Cline W. R (1979). *Agrarian structure and productivity in developing countries: a study prepared for the International Labour Office within the framework of the World Employment Programme*. Johns Hopkins University Press, 248p.

Bhalla S. S. (1988). Does land quality matter? Theory and measurement. *Journal of Development Economics*, vol. 29, n° 1, pp. 45-62.

Bhalla S. S., Roy P. (1988). Mis-specification in farm productivity analysis: the role of land quality. *Oxford Economic Papers*, vol. 40, n° 1, pp. 55-73.

Carter M. R. (1984). Identification of the inverse relationship between farm size and productivity: an empirical analysis of peasant agricultural production. *Oxford Economic Papers*, vol. 36, n° 1, pp. 131-145.

Carter M. R., Wiebe K. D. (1990). Access to capital and its impact on agrarian structure and productivity in Kenya. *American Journal of Agricultural Economics*, vol. 72, n° 5, pp. 1146-1150.

Chand R., Prasanna P. L., Singh A. (2011). Farm size and productivity: Understanding the strengths of smallholders and improving their livelihoods. *Economic and Political Weekly*, pp. 5-11.

Collier P., Dercon S. (2014). African Agriculture in 50 Years: Smallholders in a Rapidly Changing World? *World Development*, Economic Transformation in Africa, n° 63, pp. 92-101.

Dowd-Uribe B. (2014). Engineering yields and inequality? How institutions and agroecology shape Bt cotton outcomes in Burkina Faso. *Geoforum*, n° 53, pp. 161-171.

Eswaran M., Kotwal A. (1986). Access to capital and agrarian production organisation. *The Economic Journal*, vol. 96, n° 382, pp. 482-498.

Feder G. (1985). The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints. *Journal of Development Economics*, vol. 18, n° 2-3, pp. 297-313.

Heltberg R. (1998). Rural market imperfections and the farm size-productivity relationship. Evidence from Pakistan. *World Development*, vol. 26, n° 10, pp. 1807-1826.

Kevane M. (1996). Agrarian structure and agricultural practice: Ty-pology and application to Western Sudan. *American Journal of Agricultural Economics*, vol. 78, n° 1, pp. 236-245.

Kimhi A. (2006). Plot size and maize productivity in Zambia: is there an inverse relationship? *Agricultural Economics*, vol. 35, n° 1, pp. 1-9.

Larson D. F., Otsuka K., Matsumoto T., Kilic T. (2014). Should African rural development strategies depend on smallholder farms? An exploration of the inverse-productivity hypothesis. *Agricultural Economics*, vol. 45, n° 3, pp. 355-367.

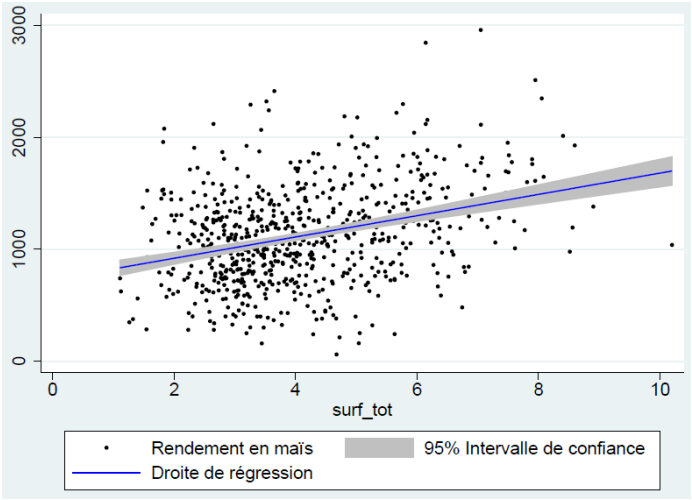
Le Cotty T., Maître d'Hôtel E., Soubeyran R., Subervie J. (2018). Linking risk aversion, time preference and fertilizer use in Burkina Faso. *The Journal of Development Studies*, vol. 54, n° 11, pp. 1991-2006.

Sawadogo H., Bock L., Lacroix D., Zombre N. P. (2008). Restauration des potentialités de sols degradés à l'aide du zaï et du compost dans le Yatenga (Burkina Faso). *Biotechnologie, Agronomie, Société et Environnement*, vol. 12, n° 3, pp. 279-290.

Zaibet L. T., Dunn E. G. (1998). Land tenure, farm size, and rural market participation in developing countries: the case of the Tunisian olive sector. *Economic Development and Cultural Change*, vol. 46, n° 4, pp. 831-848.

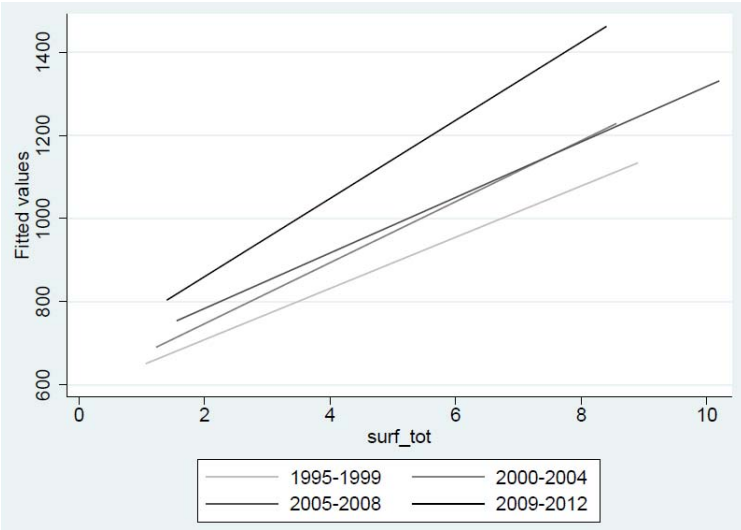
ANNEXES

Figure 7. **Relation entre productivité du maïs et surface totale au Burkina Faso** (moyennes par province et par an)



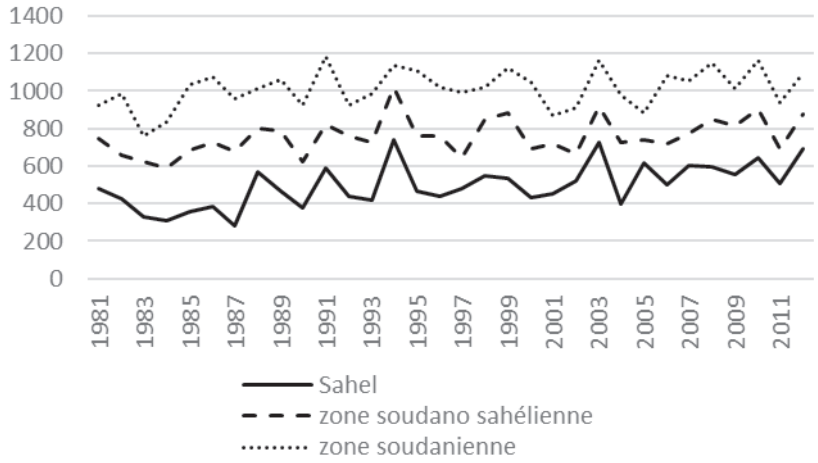
Source : les auteurs.

Figure 8. **Évolution de la relation entre productivité des céréales et surface totale au Burkina Faso**



Source : les auteurs.

Figure 9. **Cumul pluviométrique annuel au Burkina Faso (1980-2012)**



Source : les auteurs.

Tableau 3. **Estimations GMM des rendements de chaque culture en fonction du prix de la culture**

	Maïs	Mil	Sorgho
Constante	9.54	14.87 ***	9.08 *
	(0.96)	(3.40)	(1.91)
Rendement décalé	-0.12	-0.06	-0.05
	(-1.31)	(-1.10)	(-0.93)
Surface cultivée	46.44 ***	27.63 ***	26.33 ***
	(2.39)	(2.95)	(2.64)
Existence de coton	645.35 ***	132.02	199.28 **
	(2.75)	(1.23)	(1.70)
Cumul pluviométrique	0.04	0.27 ***	0.32 ***
	(0.29)	(4.02)	(4.40)
Prix de la céréale	5.13 ***	2.55 ***	3.53 ***
	(6.60)	(7.08)	(8.53)

*Notes : t-test entre parenthèses ; * (p < 0,1) ; ** (p < 0,05) ; ***(p < 0,01)*

Source : les auteurs.