

Poultry farmer response to disease outbreaks in smallholder farming systems in southern Vietnam

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23 **Abstract:** Avian influenza outbreaks have been occurring on smallholder poultry farms in Asia
24 for two decades. Farmer responses to these outbreaks can slow down or accelerate virus
25 transmission. We used a longitudinal survey of 53 small-scale chicken farms in southern
26 Vietnam to investigate the impact of outbreaks with disease-induced mortality on harvest rate,
27 vaccination, and disinfection behaviors. We found that in small broiler flocks (≤ 16 birds/flock)
28 the estimated probability of harvest was 56% higher when an outbreak occurred, and 214%
29 higher if an outbreak with sudden deaths occurred in the same month. Vaccination and
30 disinfection were strongly and positively correlated with the number of birds. Small-scale
31 farmers – the overwhelming majority of poultry producers in low-income countries – tend to rely
32 on rapid sale of birds to mitigate losses from diseases. As depopulated birds are sent to markets
33 or trading networks, this reactive behavior has the potential to enhance onward transmission.

34

35 **One sentence summary:** Longitudinal monitoring of poultry farms in southern Vietnam reveals
36 that when outbreaks occur with symptoms similar to highly pathogenic avian influenza, farmers
37 respond by sending their chickens to market early.

38 **Keywords:** epidemiology, poultry, avian influenza, Southeast Asia, behavioral epidemiology,
39 health behavior, health economics, vaccination

40 **Abbreviations:**

41 AIC: Akaike Information Criterion

42 AI: avian influenza

43 CI: confidence interval

44 CM-LPAH: Ca Mau sub-Department of Livestock Production and Animal Health

45 HPAI: highly pathogenic avian influenza

46 MGAM: mixed-effects general additive model

47 ONS: outbreak with no sudden death

48 OS: outbreak with sudden death

49 OR: odds ratio

50 **Introduction**

51 Livestock production systems have been a major driver of novel pathogen emergence events
52 over the past two decades (Gao et al., 2013; Guan et al., 2002; Rohr et al., 2019). The conditions
53 enabling the emergence and spread of a new disease in the human population partly depend on
54 human behavioral changes, like hygiene improvements or social distancing, in the face of
55 epidemiological risks (Funk, Salathe, & Jansen, 2010). The same observation applies to disease
56 emergence and spread in livestock populations as farmers adapt their farm management to
57 maximize animal production and welfare while limiting cost in a constantly changing ecological
58 and economic environment (Chilonda & Van Huylenbroeck, 2001).

59 Poultry farming generates substantial risk for emergence of novel infectious diseases. It is
60 now the most important source of animal protein for the human population and the industry is
61 changing rapidly (FAOSTAT, 2019). The link between poultry sector expansion and pathogen
62 emergence is exemplified by the worldwide spread of the highly pathogenic form of avian
63 influenza (AI) due to the H5N1 subtype of influenza A, after its initial emergence in China in
64 1996 (Guan et al., 2002; Guan & Smith, 2013). Highly Pathogenic Avian Influenza (HPAI)
65 causes severe symptoms in the most vulnerable bird species (including chicken, turkey, and
66 quail), with mortality rates as high as 100% reported in broiler flocks (OIE, 2018). Some
67 subtypes of AI viruses have caused infection in humans, including H5N1, H5N6, H7N9 and
68 H9N2, with potentially severe illness and, in the cases of H7N9 and H5N1, a high case-fatality
69 rate (Chen et al., 2013; Claas et al., 1998; Peiris et al., 1999; Yang, Mok, Peiris, & Zhong, 2015).
70 So far, reports of human-to-human transmission of these subtypes of influenza have been either
71 absent or anecdotal, but the risk that they make the leap to a human pandemic is a persistent if
72 unquantifiable threat to public health (Imai et al., 2012). While HPAI does not persist in poultry

73 populations in most affected countries, it has become endemic in parts of Asia and Africa and is
74 periodically re-introduced into other areas like Europe and North America (Lai et al., 2016; Li et
75 al., 2014). In affected countries, major factors influencing HPAI epidemiology appear to be farm
76 disinfection, poultry vaccination, and marketing of potentially infected birds through trade
77 networks, all of which depend on farmers' management decisions (Biswas et al., 2009; Desvaux
78 et al., 2011; Fasina, Rivas, Bisschop, Stegeman, & Hernandez, 2011; Henning et al., 2009; Kung
79 et al., 2007).

80 It is still unclear how and to what extent changes in outbreak risk or mortality risk affect
81 the behavior of poultry farmers. An anthropological study in Cambodia showed that high levels
82 of farmer risk awareness associated with HPAI did not translate into major changes in their
83 farming practices (Hickler, 2007). Qualitative investigations conducted in Vietnam, Bangladesh,
84 China, and Indonesia reported that farmers sometimes urgently sell or cull diseased poultry
85 flocks as a way to mitigate economic losses, but evidence of this behavior's onward
86 epidemiological impact was not available (Biswas et al., 2009; Delabougline et al., 2016;
87 Padmawati & Nicther, 2008; Sultana et al., 2012; Zhang & Pan, 2008). Additionally, it is
88 unknown whether poultry farmers increase application of disinfection practices or vaccination
89 rates against avian influenza in response to disease outbreaks occurring in their flocks. Changes
90 in farm management caused by variations in epidemiological risk have not been quantified for
91 any livestock system that we are aware of, primarily because of the lack of combined
92 epidemiological and behavioural data in longitudinal studies of livestock disease (Hidano,
93 Enticott, Christley, & Gates, 2018). Ifft et al. compared the evolution of chicken farm sizes and
94 disease prevention in administrative areas with different levels of HPAI prevalence in Vietnam
95 (Ifft, Roland-Holst, & Zilberman, 2011), and Hidano et al. modelled the effect of cattle mortality

96 and production performance on the frequency of sales and culling in New Zealand dairy farms
97 (Hidano & Gates, 2019). One limitation of these two studies is that the dynamics were observed
98 over year-long time steps, which does not allow for a precise estimation of the timing of farmer
99 response after the occurrence of disease outbreaks and the potential feedback effect of this
100 response onto the resulting outbreaks or epidemics.

101 Vietnam has suffered human mortality and economic losses due to HPAI. The disease has
102 been endemic in the country since its initial emergence in 2003-2004 (Delabougline et al., 2017).
103 Small-scale poultry farming is practiced by more than seven million Vietnamese households,
104 mostly on a scale of fewer than 100 birds per farm (General Statistics Office of Vietnam, 2017).
105 In addition to HPAI, other infectious diseases severely affect this economic sector, including
106 Newcastle disease, fowl cholera, and Gumboro, which are all endemic despite the availability of
107 vaccines for their control (OIE, 2019).

108 We present a longitudinal study of small-scale poultry farms where we aimed to
109 characterize the effect of disease outbreaks on livestock harvest rate (i.e. rate of removal by sale
110 or slaughter) and on two prevention practices, vaccination and farm disinfection. This
111 longitudinal farm survey was conducted on small-scale poultry farms in the Mekong river delta
112 region of southern Vietnam (Delabougline et al., 2019).

113

114 **Results**

115 Fifty three farms were monitored from June 2015 to January 2017. Monthly questionnaires were
116 used to collect farm-level information on poultry demographics (number, introduction, death and
117 departure of birds), mortality (cause of death, observed clinical symptoms) and management by
118 farmers. The main poultry species kept on these farms was chicken, with ducks and Muscovy

119 ducks as the other two primary relevant species held. Farmers kept an average number of 79
120 chickens, 53 ducks and 7 Muscovy ducks per farm over the 20-month study period. Each farm's
121 poultry were classified into "flocks", defined as groups of birds of the same age, species, and
122 production type. **Figure 1** illustrates the farms' structure and dynamics. Broiler chicken flocks
123 were kept for 15.5 weeks on average after which most chickens were harvested and a minority
124 was consumed or kept on the farm for breeding and egg production (Delabougline et al., 2019).

125 We fit mixed-effects general additive models (MGAM) with three different dependent
126 variables: a "harvest model" of the probability of harvesting (i.e. selling or slaughtering) chicken
127 broiler flocks at a particular production stage (data points are flock-months), an "AI vaccination
128 model" of the probability of performing AI vaccination on chicken broiler flocks which had
129 never received AI vaccination (data points are flock-months), and a "disinfection model" of the
130 probability of disinfecting farm facilities (data points are farm-months). Disease outbreaks were
131 included in each model as independent categorical variables. Disease outbreaks refer to the
132 occurrence of poultry mortality attributable to an infectious disease in the corresponding farm at
133 different time intervals before the corresponding month. Specifically, outbreaks were defined by
134 the death of at least two birds of the same species with similar clinical symptoms in the
135 corresponding farm in the same month, one month prior, and two months prior. For the harvest
136 model, only outbreaks in chickens were considered. For the AI vaccination model, outbreaks in
137 chickens and outbreaks in any other species were included as two separate covariates. For the
138 disinfection model, outbreaks in any of the species present in the farm were considered. In
139 chickens, outbreaks with "sudden deaths" (i.e. the death of chickens less than one day after the
140 onset of clinical symptoms) are considered as being indicative of HPAI infection (Mariner et al.,
141 2014). Therefore, we created two sub-categorical variables for outbreaks in chickens, with

142 sudden deaths (OS, “outbreaks sudden”) and with no sudden deaths (ONS, “outbreaks not
143 sudden”). The three dependent variables are likely influenced by several other farm-, flock-, and
144 time-related factors, justifying the inclusion of control covariates which are reported in **Table 1**
145 and described in detail in the “**Materials and Methods**”.

146 A total of 1656 broiler chicken flock-months were available for analysis. They belonged
147 to 391 chicken flocks present on 48 farms. In 18.8% of flock-months non-sudden outbreaks
148 (ONS) were observed in chickens on the same farm, 1.6% of flock-months saw sudden outbreaks
149 (OS) in chickens on the same farm, and 7.2% of flock-months saw disease outbreaks in poultry
150 of other species on the same farm (**Table 1**). The percentages are very similar for outbreaks
151 occurring one month prior and two months prior since they are averaged over similar sets of
152 months, with differences mostly related to outbreak frequency in the two first months and two
153 last months of the study period. Additional descriptive statistics on control covariates are
154 described in **Table 1**. Out of 1656 broiler chicken flock months, 1503 flock-months were
155 selected for the harvest analysis after excluding data points with new-born chicks and flock-
156 months in which all the chickens had died (see **Materials and Methods**). No harvest occurred in
157 995 flock-months, complete harvest occurred in 258 flock-months, and partial harvest occurred
158 in 250 flock-months. The probability of harvest during a month, with partial harvests weighted
159 appropriately, was 23.9%. Excluding flock-months of already vaccinated chickens (and some
160 with missing data), 1318 flock-months were selected for the AI vaccination analysis (see
161 **Materials and Methods**). AI vaccination was performed in 7.5% (99/1318) of flock-months.
162 The 99 vaccinated flocks were from 29 different farms (out of 48 farms keeping broiler
163 chickens). For the disinfection model, 858 farm-months belonging to 52 farms were included
164 (see **Materials and Methods**). During 552 farm-months the farm was fully disinfected, during

165 259 farm-months the farm was not disinfected at all, and during 47 farm-months disinfection was
166 performed for some (but not all) of the flocks present in the farm. The probability of disinfection
167 during a month, with partial disinfections weighted appropriately, was 67.4%. The best fit
168 statistical models and their parameter values are summarized in **Table 2**. Fitted spline functions
169 cannot be elegantly summarized by their coefficients and are displayed graphically in **Figures 2**
170 **and 3.**

171 The harvest model showed support for associations between flock- and farm-level
172 covariates, particularly the difference between flock age and age at maturity and the probability
173 of harvesting broiler chickens. The model explained 34.2% of the observed deviance. There was
174 no statistical support for a temporal auto-correlation of the probability of harvest of broiler
175 chicken flocks on a given farm (**Table 2**). As the interaction term between flock size (n) and
176 outbreak occurrence was significant ($p < 0.01$) but difficult to interpret (displayed in
177 **Supplementary File 1**), we separated the flocks into large and small. A threshold value of 16
178 birds per flock gave the lowest Akaike Information Criterion (AIC) (when using a categorical
179 variable indicating small flock or large flock), and flocks of 16 birds or fewer (52% of all flocks)
180 were designated as small while flocks of 17 or more (48% of all flocks) were designated as large.
181 As expected, the probability of harvest was found to be strongly dependent on the difference (δt)
182 between the flock age and the anticipated age at maturity, with older flocks being more likely to
183 be sold. The probability of harvest was close to zero when $\delta t < -15$ weeks, i.e. flocks that are
184 more than 15 weeks away from maturity. The probability of harvest increased steeply from $\delta t = -$
185 10 to $\delta t = 0$. For $\delta t > 0$ (flocks past their age at maturity), the probability of harvest was
186 consistently high but lower than 100% and did not depend on age. Larger flocks had a steeper
187 increase in harvest probability as a function of δt ; once past the age at maturity ($\delta t > 0$), the

188 estimated probability of harvest for large flocks was higher (interquartile range: 41% – 61%)
189 than for small flocks (interquartile range: 30% – 41%) (**Figure 2**).

190 Disease outbreaks substantially affected the likelihood of harvest of broiler chickens. The
191 probability of harvest of small flocks was significantly higher on farms that had experienced a
192 non-sudden outbreak (ONS) in chickens in the same month (odds ratio (OR) = 2.06; 95%
193 confidence interval (CI): 1.23 - 3.45) or the previous month (OR=2.06; 95% CI: 1.17 - 3.62) and
194 was lower on farms that had experienced an ONS in chickens two months prior (OR=0.41; 95%
195 CI: 0.19 - 0.92). The probability of harvest of small flocks was much higher on farms that had
196 experienced a sudden outbreak (OS) in the same month (OR=9.34: 95% CI: 2.13 - 40.94). We
197 used the fitted model to predict the mean harvest proportion in the study population with and
198 without outbreak. Estimated mean harvest proportions of small flocks were 17% (no outbreak),
199 28% (ONS), and 56% (OS) when considering outbreaks occurring in the same month; this
200 corresponded to harvest increases of 56% and 214% for ONS and OS outbreaks, respectively.
201 Estimated mean harvest proportion was 18% (no outbreak) and 28% (ONS) when considering
202 outbreaks one month prior; this corresponded to a 56% increase in harvest in case of ONS one
203 month prior. Mean harvest proportions were 20% (no outbreak) and 11% (ONS) when
204 considering outbreaks two months prior, indicating a 47% decrease in harvest in case ONS two
205 months prior. For large flocks, ONS in chickens (in any month current or previous) did not have
206 any effect on the harvest of broiler chickens (the removal of ONS variables decreased the model
207 AIC). The occurrence of OS in chickens one month prior may be positively associated with early
208 harvest with an estimated 76% increase in harvest proportion (OR=3.89; 95% CI: 0.82 - 18.46;
209 p=0.09). However we do not have sufficient statistical power to support this association. In the
210 last six months of data collection, farmers were asked to indicate the destination of harvested

211 birds. Based on these partial observations, flocks harvested during or one month after outbreaks
212 in chickens (OS or ONS) were more likely to be sold to traders and less likely to be slaughtered
213 at home (**Table 3**). The likelihood of harvest was also positively correlated with the number of
214 other broiler chickens present on the farm (**Supplementary File 1**, $p < 0.01$). It was not found to
215 be affected by the concomitant introduction of other flocks, vaccination status, or calendar time
216 (T). The farm random effect was significant for large flocks ($\sigma = 0.74$; 95% CI: 0.47 - 1.17) and
217 not significant for small flocks.

218 The number of outbreaks with sudden deaths is relatively small (11 small flock-months
219 and 14 large flock-months occurred on farms experiencing an OS in the same month) and OS are
220 potentially subject to misclassification, depending on how regularly farmers check on their
221 chickens. Therefore, in order to ensure the robustness of our result, we conducted a separate
222 analysis with merged OS and ONS categories. The results are displayed in **Supplementary File**
223 **2** and **Figure 2-figure supplement 1**. The probability of harvest of small flocks was
224 significantly higher on farms that had experienced an outbreak in chickens in the same month
225 (Odds ratio (OR) = 2.34; 95% CI: 1.43 - 3.81) or the previous month (OR=1.96; 95% CI: 1.14 -
226 3.37) and was lower in farms that had experienced an outbreak in chickens two months prior
227 (OR=0.45; 95% CI: 0.22 - 0.92). For large flocks, there was no statistical support for outbreaks
228 in chickens having an effect on the harvest of broiler chickens.

229 The AI vaccination model showed support for an effect of flock size on vaccination,
230 while explaining 71.9% of the observations' deviance. The likelihood of broiler chicken
231 vaccination against AI strongly increased with flock size; probability of vaccination was almost
232 zero for flocks of 16 birds or fewer and nearly 100% for flocks of more than 200 birds (**Figure**
233 **3.A**). Vaccination was preferentially performed at 4.3 weeks of age (**Figure 3.B**). Flocks kept

234 indoors or in enclosures had a substantially higher chance of being vaccinated than flocks
235 scavenging outdoors ($OR = 24.6$; CI: 6.32 - 95.6). Harvested flocks were less likely to receive an
236 AI vaccination ($OR = 0.01$; CI: 0 - 0.37). The likelihood of AI vaccination was dependent on
237 calendar time: it increased over the September-January period and decreased during the rest of
238 the year (**Figure 3.C**). There was no statistical support for a temporal auto-correlation of the
239 probability of vaccination of broiler chicken flocks against AI on a given farm. The farm random
240 effect was significant ($\sigma = 2.86$; CI: 1.88 – 4.35). We failed to obtain convergence when fitting
241 the specific effects of OS and ONS in chickens, so we used an aggregate variable “outbreak in
242 chickens” instead (**Table 2**). Broiler chicken flocks were more likely to be vaccinated if an
243 outbreak had occurred in the same month in other species ($OR = 4.62$; CI: 1.08 - 19.72; $p=0.04$)
244 and less likely to be vaccinated if an outbreak had occurred two months prior in chickens ($OR =$
245 0.27; CI: 0.08 - 0.89; $p=0.03$). These two effects were weakly significant and should be
246 interpreted with caution (**Table 2**). The coefficients for interaction terms between outbreak
247 occurrence and flock size were not significantly different from zero. The number of broiler
248 Muscovy ducks present in the farm had a negative effect ($p = 0.03$) and the number of layer
249 ducks and layer Muscovy ducks had a positive effect (both $p = 0.03$) on the probability of AI
250 vaccination (**Table 2**).

251 The disinfection model showed evidence that larger farms were more likely to report
252 routine disinfection of their premises; the model explained 61.9% of the observations’ deviance.
253 Probability of disinfection on farms was auto-correlated in time (likelihood ratio test for 1-month
254 AR-model on residuals; $p < 0.0001$); this was not observed for the harvest or vaccination models
255 (both $p > 0.3$). Consequently, the disinfection model was improved by fitting an AR-1
256 autoregressive model using the "gamm" routine of the "mgcv" R package. The estimated AR-1

257 autoregressive coefficient was high ($\rho = 0.71$). The likelihood of disinfection of farm facilities
258 increased with the number of layer-breeder hens (OR = 1.3; CI: 1.12 - 1.51; p = 0.001), layer-
259 breeder ducks (OR = 1.25; CI: 1.02 - 1.53; p = 0.03), and to a lesser extent broiler chickens
260 (OR=1.07; CI: 1.01 - 1.13; p = 0.02) present on the farm (**Table 2**). Farm disinfection appeared
261 to have a seasonal component. It was least likely in October-November and most likely in the
262 January-April period (**Figure 3D**). It was not found to be affected by the occurrence of outbreaks
263 (no decrease in AIC when including outbreak occurrence).

264

265 **Discussion**

266 Regions like the Mekong river delta combine high human population density, wildlife
267 biodiversity, and agricultural development. As such, they are considered hotspots for the
268 emergence and spread of novel pathogens (Allen et al., 2017). The high density of livestock
269 farmed in semi-commercial operations with limited disease prevention practices further increases
270 the risk of spread of emerging pathogens in livestock and their transmission to humans (Henning
271 et al., 2009). In-depth studies of poultry farmers' behavioral responses to disease occurrence in
272 animals are needed to understand how emerging pathogens – especially avian influenza viruses –
273 may spread and establish in livestock populations and how optimal management policies should
274 be designed. To the best of our knowledge, this study is the first to provide a detailed and
275 quantified account of the dynamics of livestock management in small-scale farms and its
276 evolution in response to changing epidemiological risks shortly after disease outbreaks occur.
277 While our analysis was performed on a geographically restricted area, the decision-making
278 context of the studied sample of farmers is likely to be applicable to a wide range of poultry
279 producers in low- and middle-income countries. Small-scale poultry farming, combining low

280 investments in infrastructure, no vertical integration, and subject to limited state control on
281 poultry production and trade, is common in most regions affected by avian influenza, in
282 Southeast Asia, Egypt, and West Africa (Burgos, Hinrichs, Otte, Pfeiffer, Roland-Holst, et al.,
283 2008; Hosny, 2006; Obi, Olubukola, & Maina, 2008; Sudarmarman, Rich, Randolph, & Unger,
284 2010). Additional longitudinal surveys using a similar design should be carried out in other
285 countries and contexts to assess the presence or absence of the behavioral dynamics observed
286 here.

287 In our longitudinal study, owners of small chicken broiler flocks resorted to early
288 harvesting of poultry, also referred to as depopulation, as a way to mitigate losses from
289 infectious disease outbreaks. The revenue earned from the depopulation of flocks might be low,
290 either because birds are still immature or because traders use disease symptoms as an argument
291 to decrease the sale price. Nevertheless, depopulation allows the farmer to avoid a large revenue
292 loss resulting from disease-induced mortality or the costs of management of sick or dead birds.
293 More importantly, farmers avoid the cost of feeding chickens at high risk of dying and prevent
294 the potential infection of subsequently introduced birds. Our results also suggest that the
295 depopulation period, which lasts approximately two months, is followed by a “repopulation”
296 period during which farmers lower their harvest rate, possibly to increase their pool of breeding
297 animals in order to repopulate their farm.

298 The epidemiological effect of chicken depopulation is likely twofold: on the one hand it
299 may slow the transmission of the disease on the farm, since the number of susceptible and
300 infected animals is temporarily decreased (Boni, Galvani, Wickelgren, & Malani, 2013); on the
301 other hand, since most poultry harvested during or just after outbreaks were sold to itinerant
302 traders or in markets, depopulation increases the risk of dissemination of the pathogens through

303 trade circuits (Delabougline & Boni, 2020). There is epidemiological evidence that poultry farms
304 can be contaminated with HPAI through contact with traders who purchase infectious birds and
305 that infectious birds can contaminate other birds at traders' storage places and in live bird
306 markets (Biswas et al., 2009; Guillaume Fournié et al., 2016; Kung et al., 2007). Overall,
307 chicken depopulation may reduce local transmission at the expense of long-distance
308 dissemination of the pathogen. The rapid sale of sick birds also exposes consumers and actors of
309 the transformation and distribution chain (traders, slaughterers, retailers) to an increased risk of
310 infection with zoonotic diseases transmitted by poultry, like avian influenza (G. Fournié, Hoeg,
311 Barnett, Pfeiffer, & Mangani, 2017). Large flocks appear to be less readily harvested upon
312 observation of disease mortality. Farmers may depopulate large flocks only upon observation of
313 sudden deaths, but the number of observations in our study is too small to demonstrate statistical
314 significance of this effect. The likely reason for this difference is that the sale and replacement of
315 larger flocks incurs a higher transaction cost. While small flocks are easily collected and
316 replaced by traders and chick suppliers in regular contact with farmers, the rapid sale of larger
317 flocks probably requires the intervention of large-scale traders or several small-scale traders with
318 whom farmers have no direct connection, and who may offer a lower price per bird. When farm
319 production increases, farmers tend to rely on pre-established agreements with traders,
320 middlemen, or hatcheries on the sale dates in order to reduce these transaction costs, giving them
321 little possibility to harvest birds at an earlier time (Catelo & Costales, 2008).

322 The timing of harvest of broiler chickens is also affected by farm-related factors, as
323 shown by the significance of the farm random effect in large flocks. Indeed, farmers have
324 different economic strategies, some aiming at optimizing farm productivity and harvesting
325 broilers as soon as they reach maturity, and others using their poultry flocks as a form of savings

326 and selling their poultry whenever they need income or when prices are high (ACI, 2006). For
327 the latter category, the sale of chickens presumably depends on variables which were not
328 captured in this study, like changes in market prices, economic shocks affecting the household, a
329 human disease affecting a member of the household, or celebrations. Those variables should be
330 captured in future surveys in order to improve the predictive power of harvest models. Another
331 limit of the model is the use of a proxy of the chicken weight combining age, age at maturity,
332 and flock size, rather than the actual weight, which is difficult to monitor in a longitudinal study
333 of this size.

334 While government-supported vaccination programs have been proposed as a suitable tool
335 to control AI in small scale farms with little infrastructure (FAO, 2011), in this survey AI
336 vaccination was almost exclusively performed in large flocks kept indoors or in an enclosure.
337 Vaccination against AI is believed to be inexpensive for farmers as vaccines are supplied for free
338 by the sub-department of animal health of Ca Mau province and performed by local animal
339 health workers. However, vaccination may still involve some fixed transaction cost as farmers
340 have to declare their flocks to the governmental veterinary services beforehand. Also it is
341 possible that small flocks, being less likely to be sold to distant larger cities (Tung & Costales,
342 2007), are less likely to have their vaccination status controlled, making their vaccination less
343 worthwhile from the farmers' perspective. Crucially, it is these smaller flocks that are more
344 likely to be sold into trading network during outbreaks. Finally, farmers' willingness to expand
345 their production, invest in farm infrastructure, and implement AI prevention are likely correlated.
346 Farms with a large breeding-laying activity tend to invest more in preventive actions
347 (disinfection and vaccination) compared to farms specialized in broiler production. This may

348 reflect a higher individual market value of layer-breeder hens compared to broiler chicks, making
349 their protection more worthwhile.

350 While vaccination against AI and disinfection appear to depend on individual farmer
351 attitude, as shown by the significance of the farm random effects, they still vary over time when
352 viewed across all farms (**Figure 1**). Contrary to harvesting behavior, these preventive actions
353 have a seasonal component (**Figure 3.C and 3.D**) indicating a willingness to maximize the
354 number of vaccinated broiler chickens and the protection against other diseases during the
355 January-March period. The January-March period is the period of lunar new year celebrations in
356 Viet Nam, commonly associated with higher poultry market prices and an increased risk of
357 disease transmission, as has been observed for avian influenza (Delabouglise et al., 2017; Durand
358 et al., 2015). In response, farmers tend to invest more in disease prevention practices at this time
359 and veterinary services provide more vaccines and disinfectant for free. Farm disinfection has a
360 significant temporal autocorrelation component and is unaffected by disease outbreaks,
361 indicating that farmers are slower at adapting this practice to changing conditions. Some events
362 may affect the frequency of vaccination and disinfection on a long time frame. For example, the
363 peak in AI vaccination observed at the end of 2015 can be interpreted as a part of a long-term
364 response to the high HPAI incidence reported in early 2014 (Delabouglise et al., 2017). The time
365 period of the present study is too short to provide a statistical support for these long term
366 dynamics.

367 The data from this study were recorded at farm level on monthly basis, which limits the
368 risk of recall bias. It was an easy task for farmers participating in the survey to report the number
369 of deaths and associated clinical symptoms. We cannot, however, totally exclude the risk of
370 misclassification of disease outbreaks, especially the misclassification of outbreaks in chickens

371 as “sudden”, as it is influenced by the frequency of inspection of chickens flocks by farmers and
372 other members of the households.

373 The main result of the study is that, as poultry flock size decrease, farmers increasingly
374 rely on depopulation rather than preventive strategies to limit economic losses due to infectious
375 diseases. In the current context, depopulation mainly results in the rapid transfer of potentially
376 infected chickens to trade systems, increasing the risk of pathogen dissemination. In response,
377 governments may use awareness campaigns directed at actors of poultry production systems to
378 communicate information on the public health risks associated with the trade of infected birds.

379 However, if the economic incentives for depopulating are high enough, communication
380 campaigns may fail to produce noticeable results. Small-scale farmers could play an active role
381 in the control of emerging infectious diseases if they were given the opportunity to depopulate
382 their farm upon disease detection without disseminating pathogens in trade circuits, as theoretical
383 models predict that depopulation can maintain a disease-free status in farming areas
384 (Delabougline & Boni, 2020). Policymakers may be able to encourage the establishment of
385 formal trade agreements enabling and encouraging “virtuous” management of disease outbreaks
386 in poultry. For example, in some areas of Vietnam, poultry originating from farms experiencing
387 disease outbreaks are partly used as feed for domestic reptiles (farmed pythons and crocodiles) or
388 destroyed with the support of larger farms (Delabougline et al., 2016).

389 The last 23 years of emerging pathogen outbreaks and zoonotic transmissions failed to
390 prepare us for the epidemiological catastrophe that we are witnessing in 2020. Multiple subtypes
391 of avian influenza viruses have crossed over into human populations since 1997 (Gao et al.,
392 2013; Lai et al., 2016), all resulting from poultry farming activities. Small-scale poultry farming
393 is likely to be maintained in low- and middle-income countries as it provides low-cost protein,

394 supplemental income to rural households, and is supported by consumer preference of local
395 indigenous breeds of poultry (Burgos, Hinrichs, Otte, Pfeiffer, & Roland-Holst, 2008; Epprecht,
396 2005; Sudarman et al., 2010). If we ignore the active role that poultry farmers play in the control
397 and dissemination of avian influenza, we may miss another opportunity to curtail an emerging
398 disease outbreak at a stage when it is still controllable.

399

400 **Materials and Methods**

401 *1. Data collection*

402 An observational longitudinal study was conducted in Ca Mau province in southern Vietnam
403 (Delabougline et al., 2019; Thanh et al., 2017) with the collaboration of the Ca Mau sub-
404 Department of Livestock Production and Animal Health (CM-LPAH). Fifty poultry farms from
405 two rural communes were initially enrolled and three additional farms were subsequently added
406 to the sample in order to replace three farmers who stopped their poultry farming activity. The
407 two communes were chosen by CM-LPAH based on (1) their high levels of poultry ownership,
408 (2) their history of HPAI outbreaks, and (3) likelihood of participation in the study (Thanh et al.,
409 2017). Study duration was 20 months, from June 2015 to January 2017. Monthly Vietnamese-
410 language questionnaires were used to collect information on (1) number of birds of each species
411 and production type, (2) expected age of removal from the farm, (3) number of birds introduced,
412 removed, and deceased in the last month, (4) clinical symptoms associated with death, (5)
413 vaccines administered, (6) type of poultry housing used, and (7) disinfection activity. Each
414 farm's poultry were classified into "flocks", defined as groups of birds of the same age, species,
415 and production type (Delabougline et al., 2019). Because individual poultry cannot be given
416 participant ID numbers in a long-term follow-up study like this, a custom python script was

417 developed to transform cross-sectional monthly data into a longitudinal data set on poultry flocks
418 (Nguyen-Van-Yen, 2017).

419 Recruitment was designed to have a mix of small (20-100 birds) and large (>100 birds)
420 farms and a mix of farms that were ‘primarily chicken’ and ‘primarily duck’. As multiple poultry
421 species were present on most farms, the chicken and duck farm descriptors were interpreted
422 subjectively. The enrollment aim was to include 80% small farms among chicken farms and
423 50% small farms among ducks farms; there was approximately equal representation of chicken
424 and ducks farms, but many could have been appropriately classified as having both chickens and
425 ducks. As the residents in the two communes were already familiar with CM-LPAH through
426 routine outreach and inspections, all invitees agreed to study participation. The farm sizes and
427 poultry compositions were representative of small-scale poultry ownership in the Mekong delta
428 regions, but other potential selection biases in the recruitment process could not be ascertained.
429 No sample size calculation was performed for the behavioral analysis presented here, as we had
430 no baseline estimates of sale patterns or disease prevention activities. The duration and size of
431 the study was planned to be able to observe about 1000 poultry flocks (all species and production
432 types included).

433 ***2. Selection of observations***

434 For the "harvest model" and "AI vaccination model", we focused our analysis on broiler chicken
435 flocks, since chicken was the predominant species in the study population, the overwhelming
436 majority of chicken flocks were broilers, and their age-specific harvest was easier to predict than
437 the harvest of layer-breeder hens. Additionally, only six layer-breeder chicken flocks were
438 vaccinated against AI during the study period. Observations made in the two first months of the
439 study were discarded since, during these two months, it was unknown whether farms had
440 previously experienced outbreaks.

441 In the “disinfection” model, observations were farm-months. A total of 876 farm-months
442 were available for inclusion in the model. We removed farm-month with missing data on
443 disinfection performed by farmers (18 farm-months) so 858 farm-months were used to fit the
444 disinfection model. In the “harvest” and “AI vaccination” models, observations were chicken
445 broiler flock-months. We selected all chicken flock-months more than 10 days old at the time of
446 data collection and classified by farmers as "broilers". A total of 1656 flock-months were
447 available for inclusion in the model. In the “harvest model we removed flock-months which were
448 less than 20 days old at the time of data collection. This 20-day threshold was chosen because
449 some newborn flocks below this age were partly sold, not for meat consumption but for
450 management on other farms. Also, we removed flock-months where no chickens were available
451 for harvest because they had all died in the course of the month (25 flock-months). In total, 153
452 flock-months were removed and 1503 flock-months were used to fit the harvest model. In the
453 “AI vaccination” model, we removed flock-months of flocks which had already been vaccinated
454 against avian influenza in a previous month, since vaccination is usually performed only once
455 (among the 338 vaccinated flocks, only 8 were vaccinated a second time). We also removed
456 flock-months whose housing conditions were not reported (4 flock-months). In total, 338 flock-
457 months were removed and 1318 flock-months were used to fit the AI vaccination model.

458 *3. Selection of covariates*

459 A disease outbreak was defined as the death of at least two birds of the same species – on the
460 same farm, in the same month, with similar clinical symptoms – as this may indicate the
461 presence of an infectious pathogen on the farm. Our definition of outbreaks with sudden deaths
462 encompassed all instances of outbreaks where chicken deaths were noticed without observation
463 of any symptoms beforehand. Since farmers, or their family, check on their poultry at least once

464 per day, it was assumed that these “sudden deaths” corresponded to a time period of less than
465 one day between onset of symptoms and death. For both the harvest and AI vaccination models,
466 we assumed the effect of outbreaks on the dependent variable may be affected by the size of the
467 considered flock (n). Consequently, we included this interaction term in the analysis.

468 The three dependent variables are likely affected by several farm-, flock-, and time-
469 related factors, justifying the inclusion of several control covariates in the multivariable models,
470 summarized in **Table 1**. For the harvest model, the main control variable is, logically, (1) the
471 body weight of chickens, as broiler chickens are conventionally harvested after a fattening period
472 upon reaching a given weight. Since the chicken weight was not collected during the survey, we
473 used the difference between the current flock age t and the anticipated age at maturity t^*
474 indicated by farmers in the questionnaire. Hereafter we use $\delta t = t - t^*$ for this difference. The
475 shape of the function linking δt and harvest may depart from linearity and is affected by the
476 chicken breed, which determines the growth performance. Since information on chicken breed
477 was not collected we used the age at maturity t^* and the logarithm of flock size ($\log(n)$) as proxy
478 indicators of the growing performance of the breed and built a proxy body weight variable as a
479 multivariate spline function of δt , t^* and n (Burgos, Hinrichs, Otte, Pfeiffer, & Roland-Holst,
480 2008). 20% of flock-months had missing value for t^* . Since there was little within-farm variation
481 in t^* (2 months of difference at most between two flocks of the same farm), missing values were
482 replaced by the median t^* in the other flocks of the corresponding farm. (2) The calendar time T
483 was included as an additional smoothing spline term, since harvest may also be influenced by
484 market prices which vary from one month to the other. Control variables included as standard
485 linear terms were (1) the number of chickens kept for laying eggs or breeding - famers with a
486 large breeder-layer activity may want to keep some broilers chickens in the farm for replacing

487 the breeding-laying stock, making them less likely to harvest broilers; (2) the number of broiler
488 chickens simultaneously present in the same farm in other flocks; (3) the number of chicken
489 flocks introduced in the same month; (4) the number of chicken flocks introduced in the previous
490 month – farmers with a high number of broilers chickens or many recently introduced broiler
491 flocks may want to sell their current flocks faster in order to limit feeding expenses and
492 workload; (5) the vaccination status of the flock against AI; (6) the vaccination status of the flock
493 against Newcastle Disease (ND) – farmers may keep their vaccinated flocks for a longer period
494 as they are at lower risk of being affected by an infectious disease. We assumed the effect of
495 outbreaks on the dependent variable may be affected by the size of the considered flock (n).
496 Consequently, we included an interaction term between outbreaks and $\log(n)$ in the analysis.

497 For the AI primo-vaccination model, control variables included as smoothing splines
498 were (1) the logarithm of flock age ($\log(t)$) - vaccination may be preferentially done early in the
499 flock life, (2) the flock size n , and (3) the calendar time T - vaccination activities may be
500 intensified at particular times of the year. Control variables included as standard linear terms
501 were (1) the type of housing (free-range or confinement in pens or indoor) which affects the
502 convenience of vaccination; (2) the proportion of the flock harvested in the same month -
503 farmers might be less willing to vaccinate flocks being harvested; and the size of populations of
504 (3) broiler chickens, (4) layer-breeder chickens, (5) broiler ducks, (6) layer-breeder ducks, (7)
505 broiler Muscovy ducks and (8) layer-breeder Muscovy ducks kept in other flocks - farmers'
506 perceived risk of AI and attitude towards vaccination may be influenced by the size of the
507 poultry population at risk for AI and production type; We assumed the effect of outbreaks on the
508 dependent variable may be affected by the size of the considered flock (n). Consequently, we
509 included an interaction term between outbreaks and $\log(n)$ in the analysis.

510 For the disinfection model, control variables included as smoothing splines were (1) the
511 calendar time T - disinfection activities may be intensified at particular times of the year. Control
512 variables included as standard linear terms were the size of populations of (1) broiler chickens,
513 (2) layer-breeder chickens, (3) broiler ducks, (4) layer-breeder ducks, (5) broiler Muscovy ducks
514 and (6) layer-breeder Muscovy ducks - the farmers' attitude towards prevention may be
515 influenced by the size of the poultry population at risk of disease.

516 **4. Multivariable modelling**

517 We assumed that the events of interest, namely harvest, AI vaccination, and disinfection were
518 drawn from a binomial distribution and used a logistic function to link their probability to a
519 function of the independent covariates. Flocks were either fully vaccinated for AI or not at all, so
520 the AI vaccination variable for flock-months took only the value 0 or 1 and was, therefore,
521 treated as binary. Partial flock harvest (the harvest of only a fraction of the chickens in a given
522 flock) and partial farm disinfection (the disinfection of facilities for only a fraction of the poultry
523 flocks present in the farm) occurred in a minority of observations. Therefore, the number of
524 chickens harvested per flock-month and the number of poultry flocks disinfected per farm-month
525 were treated as binomial random variables with a number of trials equal to the flock size (for
526 harvest) and the number of flocks per farm (for disinfection). To ensure that the model was not
527 conditioned on the size of flocks and number of flocks per farm, prior weights equal to the
528 inverse of the flock size and the number of flocks in the farm (i.e. the number of trials) were used
529 in the binomial harvest model and disinfection model, respectively. The extent of over- or under-
530 dispersion in the data was investigated by fitting a quasi-binomial model in parallel (Papke &
531 Wooldridge, 1996). The resulting dispersion parameters were 0.76 (harvest model) and 0.77

532 (disinfection model), indicating moderate underdispersion, and that the estimates of our analyses
 533 are conservative.

534 Some of the included effects are non-linear in nature, and we needed to account for the
 535 intra-farm autocorrelation of the dependent variables. We therefore used a mixed-effects general
 536 additive model (MGAM) implemented in R with the "mgcv" package (Wood, Pya, & Säfken,
 537 2017). This enabled us to model the combined effect of δt , t^* , and flock size (n) on harvest time;
 538 the effect of t and n on AI vaccination; and the effect of calendar time (T) on all the dependent
 539 variables, as penalized thin plate regression splines (Wood, 2017). We specifically chose these
 540 variables because they are presumably the most important factors influencing the dependent
 541 variables and their effect could possibly be highly non-linear. All other covariates were included
 542 as parametric regression terms. We also modelled the individual effects of farms on the
 543 dependent variables as random effects.

544 The complete models linking the logit Y_{ij} of probability of realization of an event and the
 545 set of explanatory variables, for a flock-month i (harvest, vaccination for AI) or a farm-month i
 546 (disinfection) in a farm j , are described by the following set of equations:

547 Harvest model (flock-month level):

$$548 \quad Y_{ij} = \alpha + \sum_{m=0}^2 \beta^{ONS-m} X_{ij}^{ONS-m} + \sum_{m=0}^2 \beta^{OS-m} X_{ij}^{OS-m} + f_{\delta t}(\delta t_{ij}, t_{ij}^*, \log(n_{ij})) + f_T(T_{ij}) + \sum_{k=1}^6 \beta^k X_{ij}^k + \phi_j + \varepsilon_{ij} \quad (1)$$

549 AI vaccination model (flock-month level):

$$550 \quad Y_{ij} = \alpha + \sum_{m=0}^2 \beta^{ONS-m} X_{ij}^{ONS-m} + \sum_{m=0}^2 \beta^{OS-m} X_{ij}^{OS-m} + \sum_{m=0}^2 \beta^{OD-m} X_{ij}^{OD-m} + f_t(\log(t_{ij})) + f_n(\log(n_{ij})) + f_T(T_{ij}) + \sum_{k=1}^8 \beta^k X_{ij}^k + \phi_j + \varepsilon_{ij} \quad (2)$$

551 Disinfection model (farm-month level):

$$552 \quad Y_{ij} = \alpha + \sum_{m=0}^2 \beta^{O-m} X_{ij}^{O-m} + f_T(T_{ij}) + \sum_{k=1}^6 \beta^k X_{ij}^k + \varphi_j + \varepsilon_{ij} \quad (3)$$

553 The model parameters are α the model intercept; β the parametric coefficients; f a thin-plate
554 spline function; X^k the general notation for variables with linear effects; X^{O-m} , X^{OS-m} , X^{ONS-m} and
555 X^{OD-m} , categorical variables denoting presence or absence of an outbreak in the same farm m
556 months prior in any species (O), in chickens with sudden deaths (OS), in chickens with no
557 sudden deaths (ONS), and in different species (OD) respectively; n the flock size; t the current
558 age of the flock; t^* the age at maturity of the flock anticipated by the farmer; δt the difference
559 between current age and age at maturity; T the calendar time; φ the farm random effect; ε the
560 residual error term. Some variables with a highly skewed distribution (**Table 1**) were
561 transformed. Current age (t) and flock size (n) being strictly positive, they were log-transformed.
562 Farm populations of broiler and layer-breeders of different species being null or positive, they
563 were square-root transformed. Covariates included in the multivariate spline function for body
564 weight (δt , t^* , $\log(n)$) were centered and standardized. Interaction terms between outbreak
565 categorical variables and flock size $\log(n_{ij})$ were added in the Harvest and AI vaccination models.

566 Excessive multi-collinearity between covariates was assessed by estimating their variance
567 inflated factor using the "usdm" R package (Naimi, Hamm, Groen, Skidmore, & Toxopeus,
568 2014). We fitted the complete models using the whole set of covariates using restricted
569 maximum likelihood estimation. We then used a backward-forward stepwise selection, based on
570 AIC comparison, to eliminate the variables with non-significant effects (Hosmer & Lemeshow,
571 2000).

572 Arguably, one farmer is likely to maintain the same farm management from one month to
573 the next despite changes in influential covariates. Therefore, for each model, we tested the
574 presence of farm-level temporal autocorrelation by fitting two linear regression models on the
575 deviance residuals, with a fixed constant effect and with and without intra-farm AR-1 time

576 autocorrelation structure and comparing the two model fits with a log-likelihood ratio test. For
577 the “disinfection” model, the fit was significantly improved by including the autocorrelation term
578 while for the two other models it was not. Therefore, we implemented the same model fitting
579 protocol for the “disinfection” model with an additional intra-farm AR-1 time autocorrelation
580 term on the dependent variable. We used the "gamm" routine of the "mgcv" package for this
581 purpose (Wood, 2017). Since "gamm" models for binomial data are fitted with the penalized
582 quasi-likelihood approach, the AIC metric is not suitable to compare such models. Instead, we
583 implemented a stepwise removal of covariates whose t-test returned the highest probability of
584 type 1 error (p-value) until all remaining covariates had a p-value lower than 20%.

585 All analyses and graphical representations were performed with R version 3.6.1 (R core
586 team, 2014).

587 **5. Ethical statement**

588 The collaboration between the investigators (authors) and the Ca Mau sub-Department of
589 Livestock Production and Animal Health (CM-LPAH) was approved by the Hospital for
590 Tropical Diseases in Ho Chi Minh City, Vietnam. The CM-LPAH, which at the province-level is
591 the equivalent of an ethical committee for studies on livestock farming, specifically approved
592 this study.

593

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598 **Competing interests:**

599 The authors declare they do not have any conflict of interest.

600 **Data availability**

601 The study dataset is available online at <https://osf.io/ws3vu/>. DOI: 10.17605/OSF.IO/WS3VU

602

603 **Table 1. Summary statistics of variables**

Continuous variable	Min	1st quartile	Median	3rd quartile	Max
Broiler chicken flocks (n = 391)					
Number of flocks of broiler chickens per farm	2	22	36	44	75
Number of observation months per broiler flock	1	3	4	5	12
Broiler chicken flock-months (n = 1656)					
Flock size (<i>n</i>) (number of birds)	2	10	16	35	580
Anticipated age at maturity (<i>t</i> *) (weeks)	9.5	13.1	17.4	19.6	43.6
Age at the time of observation (<i>t</i>) (weeks)	1.6	6.3	12.3	19	53.6
Difference <i>t</i> - <i>t</i> * (δt) (week)	-37.2	-11.1	-5.2	1	36.1
Calendar time (<i>T</i>)	3	7	11	16	20
Proportion harvested (%)	0	0	0	33.3	100
Number of chicken flocks introduced in the same month onto the same farm	0	0	0	1	4
Number of chicken flocks introduced in the month prior onto the same farm	0	0	0	1	2
Number of broiler chickens present on the same farm in other flocks (bird)	0	10	25	61	900
Number of broiler ducks present on the same farm (bird)	0	0	0	25	3630
Number of broiler Muscovy ducks present on the same farm (bird)	0	0	0	6	80
Number of layer chickens present on the same farm (bird)	0	2	6	13	350
Number of layer ducks present on the same farm (bird)	0	0	0	0	11
Number of layer Muscovy ducks present on the same farm (bird)	0	0	0	2	30
Farm-months (n = 876)					

Number of broiler chickens (bird)	0	8	28	64	912
Number of broiler ducks (bird)	0	0	4	31	3630
Number of broiler Muscovy ducks (bird)	0	0	0	6	80
Number of layer chickens farm (bird)	0	0	4	10	358
Number of layer ducks (bird)	0	0	0	0	500
Number of layer Muscovy ducks (bird)	0	0	0	2	30
Proportion flocks farmed with disinfection (%)	0	0	100	100	100

Qualitative variable	Proportion of observations
Broiler chicken flock-months (n = 1656)	
Occurrence of outbreak with no sudden death in chickens on the same farm in the current month	18.8%
Occurrence of outbreak with sudden death in chickens on the same farm in the current month	1.6%
Occurrence of outbreak in other species on the same farm in the current month	7.2%
Confinement indoors or in enclosure	32.8%
Previously vaccinated for AI	20.2%
Previously vaccinated for Newcastle Disease	7.1%
Farm-months (n = 876)	
Occurrence of outbreak in any species	23.4%

604

605

606 **Table 2. Fitted parameters of the broiler chicken flock harvest and AI vaccination and**
 607 **farm disinfection models**

Model	Variable	Odds-ratio (with 95% CI)	p-value	
Harvest	ONS chickens*	Same month	2.06 (1.23 ; 3.45)	$< 10^{-2}$
		-1 month	2.06 (1.17 ; 3.62)	0.02
		-2 months	0.41 (0.19 ; 0.92)	0.03
	Flock size \leq 16 chickens	Same month	9.34 (2.13 ; 40.94)	$< 10^{-2}$
		-1 month	0.18 (0.01 ; 4.95)	0.32
		-2 months	0.88 (0.15 ; 5.04)	0.89
		Number of broiler chickens in the farm (square root)	1.05 (1 ; 1.11)	0.06
		combined effect of the difference between current age and age at maturity (δt) and the age at maturity (t^*) (spline transformation)	Figure 2	$< 10^{-3}$
		Same month	1.02 (0.23 ; 4.46)	0.98
	OS chickens**	-1 month	3.89 (0.82 ; 18.46)	0.09
		-2 months	3.1 (0.51 ; 18.77)	0.22
		Number of broiler chickens in the farm (square root)	1.05 (1 ; 1.11)	0.05
AI vaccination	Flock size > 16 chickens	combined effect of the difference between current age and age at maturity (δt) and the age at maturity (t^*) (spline transformation)	Figure 2	$< 10^{-3}$
		Same month	0.75 (0.29 - 1.92)	0.55
		-1 month	0.78 (0.29 - 2.11)	0.63
	Outbreak others	-2 months	0.27 (0.08 - 0.89)	0.04
		Same month	4.62 (1.08 - 19.72)	0.04

	-1 month	0.51 (0.09 - 2.89)	0.45
	-2 months	0.42 (0.06 - 2.91)	0.39
	Number of broiler chickens in the farm (square root)	0.92 (0.82 - 1.03)	0.2
	Number of broiler Muscovy ducks in the farm (square root)	0.74 (0.57 - 0.96)	0.03
	Number of layer ducks in the farm (square root)	2.95 (1.15 - 7.57)	0.03
	Number of layer Muscovy ducks in the farm (square root)	1.9 (1.07 - 3.36)	0.03
	Confinement	24.6 (6.32 - 95.6)	$< 10^{-3}$
	Proportion harvested	0.01 (0 - 0.37)	0.02
	Spline transform of the logarithm of the flock size (n)	Figure 3.A	$< 10^{-3}$
	Spline transform of the logarithm of the flock age (t)	Figure 3.B	$< 10^{-3}$
	Spline transform of the calendar time (T)	Figure 3.C	$< 10^{-3}$
Disinfection	Number of broiler Muscovy ducks in the farm (square root)	1.07 (1.01 - 1.13)	0.02
	Number of layer ducks in the farm (square root)	1.25 (1.02 - 1.53)	0.04
	Number of layer chickens in the farm (square root)	1.3 (1.12 - 1.51)	$< 10^{-3}$
	Spline transform of the calendar time (T)	Figure 3.D	$< 10^{-3}$

608 Variables with p value <0.1 are highlighted in gray

609 *ONS: Outbreak with no sudden deaths

610 **OS: Outbreak with sudden deaths

611

612 **Table 3. The destination of harvested broiler chicken flocks with or without occurrence of**
 613 **outbreaks of disease-induced mortality in chickens of the same farm in the same month or**
 614 **one month prior (%)**

Destination	No outbreak	Outbreak with no sudden death (ONS)	Outbreak with sudden death (OS)
Sale to traders	28%	45%	45%
Sale at market	5%	16%	0%
Sale to other farmers	2%	3%	0%
Sale unspecified	12%	4%	11%
Slaughter at home	36%	20%	11%
Gift	5%	8%	11%
Feed farmed pythons	5%	1%	22%
Other	7%	3%	0%

615

616

617 **Figures**

618

619 **Figure 1. History of chicken flocks present in four of the observed farms over the study**
620 **period.** Each colored line represents the period over which a single chicken flock was present on
621 the farm, with the color code indicating the production type, which may vary during the course
622 of the flock production period. The major events affecting the flocks are located with specific
623 symbols on the corresponding lines and months.

624

625 **Figure 2. Graphical representation of the relationship between the difference δt (current**
626 **flock age - flock age at maturity) and the proportion of broiler flocks harvested in the**
627 **absence (NO, green) or presence of outbreaks with disease-induced mortality, either with**
628 **sudden deaths (OS, red) or with no sudden deaths (ONS, orange).** Three different
629 **outbreak timings are considered: same month (left), one month prior (middle), and two**
630 **months prior (right). Two different classes of flock size are considered: small, <17 chickens**
631 **(top) and large, ≥ 17 chickens (bottom).** Points are the observed proportions (estimated from at
632 least two flock-months) and lines are the predictions of the fitted Harvest model, along with 90%
633 confidence bands. Model predictions with outbreaks are only displayed when fitted outbreak
634 effects have some statistical significance ($p < 0.10$) (see **Table 2**). Blue histograms correspond to
635 the number of observed flock-months in the different classes of δt (scaled to their maximum, 139
636 in the top graphs and 157 in the bottom graphs).

637

638 **Figure 3. Graphical representation of predictions of the AI vaccination and disinfection**
639 **models as functions of covariates whose effect is modeled with thin plate smooth splines.**

640 For the AI vaccination model (green) these covariates are flock size (n) (A), age (t) (B) and
641 calendar time (T) (C). For the disinfection model (orange), the covariate is calendar time (T) (D).
642 Points are the observed proportions and lines are the predictions along with the 90% confidence
643 band. In graphs C and D the proportions are displayed on the logit scale. Blue histograms
644 correspond to the number of observed flock-months in the different classes of $\log(n)$ (A) and t
645 (B) (scaled to their maximum, 402 in A and 345 in B).

646

647 **Supplementary materials**

648 **Supplementary File 1.** Fitted parameters of the original broiler chicken harvest model

649 **Supplementary File 2.** Fitted parameters of the broiler chicken harvest model with aggregated
650 effects of outbreaks with and without sudden deaths

651 **Figure 2-figure supplement 1.** Graphical representation of the relationship between the
652 difference δt (current flock age - flock age at maturity) and the proportion of broiler flocks
653 harvested in the absence (green color - NO) or presence of outbreaks with disease-induced
654 mortality (dark orange color). Three different outbreak timings are considered: same month
655 (left), one month prior (middle), and two months prior (right). Two different classes of flock size
656 are considered: small (top) and large (bottom). Points are the observed proportions (estimated
657 from at least two flock-months) and lines are the predictions of the fitted Harvest model, along
658 with 90% confidence bands. Model predictions with outbreaks are only displayed when fitted
659 outbreak effects have some statistical significance ($p < 0.10$) (see **Supplementary File 2**). Blue
660 histograms correspond to the number of observed flock-months in the different classes of δt
661 (scaled to their maximum, 139 in the top graphs and 157 in the bottom graphs).

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