European Review of Agricultural Economics Vol **47 (3)** (2020) pp. 1201–1222
doi:10.1093/erae/jbz041
Advance Access publication 5 December 2019

Farmers' heterogeneous motives, voluntary vaccination and disease spread: an agent-based model

Jaap Sok[†,*] and Egil A. J. Fischer[‡]

[†]*Department of Social Sciences, Business Economics, Wageningen University, The Netherlands* [‡]*Faculty of Veterinary Medicine, Utrecht University, The Netherlands*

Received October 2018; final version accepted August 2019

Review coordinated by Ada Wossink

Abstract

Animal health authorities responsible for effective voluntary livestock disease control need to consider the dynamic interplay between farmers' collective behaviour and disease epidemiology. We present an agent-based model to simulate vaccination scheme designs that differ in expected adverse vaccine effects, communication strategies and subsidy levels. Specific scheme designs improve the vaccine uptake by farmers at the start of a livestock disease epidemic compared with a base scheme of minimal communication and subsidy. The results suggest that motivational mechanisms activated by a well-designed risk communication strategy are equally or more effective in increasing vaccination uptake than providing more financial compensation.

Keywords: bluetongue, agent-based model, integrated choice and latent variable approach, information diffusion, intrinsic and extrinsic motivation

JEL classification: C63, D91, Q18

1. Introduction

Whilst the management of animal health starts at the farm level, a livestock disease outbreak triggers policy measures to control and even stamp out diseases. The design of these policies is hampered by externalities, imperfect information and scale economies in enforcement. With transboundary challenges calling for a harmonised response, the EU has set specific legislation for several livestock disease control measures that each member state should implement if an outbreak is observed. One such livestock disease is bluetongue, which is a vector-borne disease caused by the bluetongue virus, affecting ruminants such as cattle, sheep and goats. A large epidemic of bluetongue serotype 8 occurred

*Corresponding author: E-mail: jaap.sok@wur.nl

in Europe from 2006 to 2009. A mass emergency vaccination campaign was needed to halt the epidemic. EU member states thought differently about the optimal vaccination strategy, i.e. whether the scheme should be made mandatory or voluntary (Wilson and Mellor, 2009).

The Netherlands' animal health authorities opted in 2008 for a voluntary approach and used informational (sermon) and incentive-based (carrot) policy instruments to motivate farmers to vaccinate. Making farmers' participation voluntary reflects a governance model of sharing costs and responsibilities; it sees control of livestock diseases mainly as a task of the private sector, whereas the role of the government is to secure property rights and act as an initiator. Aligning with this perspective, regulation should be soft and optional and the regulatory levers for government are communication of information and financial incentives.

In the context of a voluntary approach, livestock disease control is effectively an interplay between the dynamics of farmers' collective behaviour and disease epidemiology. These dynamics first need to be understood and next accounted for in models that provide underpinnings for policy making. These models aim to give insights on how farmers facing a disease epidemic would respond to a voluntary approach.

In the economic livestock disease control literature, this question is often approached using principal-agent theory from information economics (Gramig, Horan and Wolf, 2009; Hennessy and Wolf, 2015). Bluetongue is a disease listed by the World Organization for Animal Health, making it a notifiable disease for which there is a legal responsibility to act. Control and eradication are thus the responsibility of government. According to principal-agent theory[1], livestock disease control is a contractual relationship between the principal – the animal health authorities – and the agents – a collective of farmers. Whilst the principal's prime interest is to control the disease transmission as efficiently as possible, the agents' interest is maximisation of utility by avoiding a disruption of business and associated economic damage. Information asymmetries between both parties are expected to occur with respect to disease status and control efforts. The mainstream economists' view is that contract problems of moral hazard and adverse selection can be solved by using the price mechanism (Eisenhardt, 1989). This assumes rational behaviour of self-interested farmers who do not internalise the positive or negative off-farm effects (externalities) of their livestock disease management on other farms.

Behavioural economists and social psychologists, however, stress the heterogeneity in people's motives and show that the price mechanism is only one form of motivation. They argue that voluntary behaviour can be motivated both intrinsically and extrinsically (Kreps, 1997, Rabin, 1998; Deci, Koestner and Ryan, 1999; Frey and Jegen, 2001). For intrinsically motivated people, the personal reward from the voluntary activity as such might be sufficient

1 One reviewer suggests that the coordination problem can also be conceptualised from a club good perspective.

to induce the behavioural change. For extrinsically motivated people, next to the price mechanism, social norms can be an additional form of motivation. Governments are increasingly adopting approaches from behavioural science (nudging and boosting) to make policy interventions based on a voluntary approach more effective and less costly (Benartzi *et al.*, 2017; Hertwig and Grüne-Yanoff, 2017). It is well-known however that financial incentives can encourage but also discourage specific behaviour (e.g. Bowles and Polanía-Reyes, 2012). These crowding-in and crowding-out effects also occur in the agricultural policy context, such as in farmers' compliance with conservation policies (Greiner and Gregg, 2011; Czap *et al.*, 2015; Kuhfuss *et al.*, 2015; Rode, Gómez-Baggethun and Krause, 2015; Dessart *et al.*, 2019). A crowding-out effect in the policy context of livestock disease control was recently reported by Sok *et al.* (2018).

We contribute to the economics of livestock disease control literature by demonstrating an alternative bottom-up agent-based modelling (or 'individual-based') approach. Agent-based models (ABMs) have been used in previous studies of a wide range of infectious livestock and plant diseases (for some recent examples, see, e.g. Pacilly *et al.*, 2018; Wiltshire, 2018). Whilst our ABM captures disease epidemiology, our focus is on modelling farmer behaviour. Existing agricultural ABMs that include a farmer behaviour component are commonly focussed on issues of land-use and structural change (Huber *et al.*, 2018). Agent-based modelling provides a flexible way to describe the process and context of vaccination decisions more realistically (Epstein, 1999; Bonabeau, 2002). An ABM enables the agents to be situated in an explicit environment that accounts for spatial (e.g. network) and temporal effects (Gilbert, 2008; Chhatwal and He, 2015).

Human decision models used in ABMs range from rational choice, social-psychological theories and simple empirical or heuristic rules with or without any theoretical foundation (An, 2012; Groeneveld *et al.*, 2017). Following Sok *et al.* (2018), we use an integrated choice and latent variable model (ICLV); such ICLV models have been suggested as promising for modelling individual behaviour in ABMs (Bruch and Atwell, 2015; Klabunde and Willekens, 2016).

The next section presents the way we modelled and simulated farmers' vaccination behaviour in the ABM starting from an existing ICLV. In Section 3, we report on our application to simulate the effectiveness of different government-initiated voluntary vaccination scheme designs, in terms of the uptake of different vaccination schemes. We are especially interested in how motivational mechanisms activated by different attributes of a vaccination scheme affect the uptake by a collective of farmers. To analyse the performance of alternative vaccination scheme designs, we use simulated bluetongue epidemics based on the 2006–2009 outbreak in The Netherlands as a case study. Section 4 presents the findings and lessons learned from the analysis.

2. Development of the model

Our starting point for modelling farmers' vaccination behaviour is the paper by Sok *et al.* (2018). The ICLV model estimated by Sok *et al.* (2018) revealed the presence of different motivational mechanisms that underlie collective behaviour of Dutch farmers and affect vaccination uptake either positively or negatively. Our ABM essentially takes these findings a step further by additionally modelling the epidemiology of disease transmission (in Section 2.2) and a social network structure (in Section 2.3) that provide farmers with information about disease risk and the vaccination behaviour of others, respectively. In Section 2.4, empirics on stated vaccination choices, indicators for social-psychological constructs, and farm and farmer characteristics are used to construct farmer profiles for the agent population in the ABM. Finally, Section 2.5 presents the heuristics used to update the vaccination probabilities in the model.

2.1. Farmers' vaccination behaviour

We formulate an individual farmer's vaccination decision as a discrete choice problem, consistent with random utility theory (for details, see, e.g. Hensher, Rose and Greene, 2005). Random utility theory states that the utility derived from participation in a vaccination scheme is the sum of utility derived from the attributes of that vaccination scheme. ICLV models are extended discrete choice models in which the random utility model is generalised Walker & Ben-Akiva (2002). In an ICLV model, the influence of attribute characteristics and also of decision-makers' individual characteristics on the choice of an alternative are estimated econometrically. The addition of decision-makers' characteristics enables behavioural representation (scores on latent constructs) in choice models. Furthermore, with the ICLV model, the probability of a particular alternative being chosen can be estimated. Both features of the ICLV model are important in developing our ABM.

Behavioural representation in choice models is commonly done by including measurements of social-psychological constructs (Ben-Akiva *et al.*, 2012). Sok *et al.* (2018) analysed farmers' preferences for five attributes of a bluetongue vaccination scheme using a choice experiment and also measured selected social-psychological constructs and farm and farmer characteristics for a sample of 211 dairy farmers in The Netherlands. Table 1 summarises each of these attributes and reports the variables that explained heterogeneity in preferences for the different attributes. The choice experiment built on Sok *et al.* (2015) who analysed farmers' intention to vaccinate against bluetongue using the attitude, injunctive norm and descriptive norm. These constructs explain preference heterogeneity consistent with the reasoned action approach[2]

2 The reasoned action approach is a decision model from social psychology, and an extension of the theory of planned behaviour. The central assumption is that a person's behaviour is determined by motivation, measured by the intention to perform the behaviour, and ability, measured by (perceived) control over the behaviour (PBC). Intention, in turn, is determined by

Table 1. Description of the five attributes of a bluetongue vaccination scheme (Sok *et al.*, 2018)

Attribute (X)	Levels (s)	Description	Preference heterogeneity explained by
Probability of adverse vaccine effects	Significant small negligible	Farmers' perceived trust and confidence in the vaccine safety, effectiveness and disease control approach in general	Descriptive norm
Government communication	No information via leaflet via veterinarian via leaflet and veterinarian	Informational policy instrument to increase the intrinsic motivation by reasoned opinions	Attitude
Government subsidy	No subsidy 10 per cent 60 per cent	Incentive-based policy instrument to increase the extrinsic motivation by compensating part of the costs	Injunctive norm, age
Vaccination costs per cow	EUR 4 EUR 8 EUR 12	Farmers' contribution to the costs of herd vaccination (excluding financial compensation)	Age
Infection probability	Significant negligible	If vaccination, the probability of herd infection becomes negligible	Attitude, injunctive norm, descriptive norm, herd size, milk production, pasture land, export of heifers, age

(Fishbein and Ajzen, 2010). Attitude is the positive or negative evaluation of vaccination, and can be based on instrumental (e.g. risk insuring) as well as experiential (e.g. avoid animal suffering) aspects (Sok *et al.*, 2015). Injunctive norm refers to perceptions of what referents of influence think should be done. Descriptive norm refers to the perceived behaviour of others (peers).

Each farmer makes the vaccination decision for only one farm. Farmers of susceptible farms observe the closeness and number of infected farms and vaccination behaviour of others within their social network. Figure 1 shows the information flow in the ABM set-up and visualises the dynamic interplay between farmers' collective behaviour and disease epidemiology.

The spatially explicit ABM was programmed in Netlogo 5.3 (Wilensky, 1999) in a two-dimensional geographical space $A \times B$ in km^2 with a total number of farms N, determined by a dairy farm density d. Each farm is placed at a random position in space. One vector season (Spring to Autumn) is simulated

a person's attitude towards the behaviour, perceived social pressure to perform the behaviour and PBC.

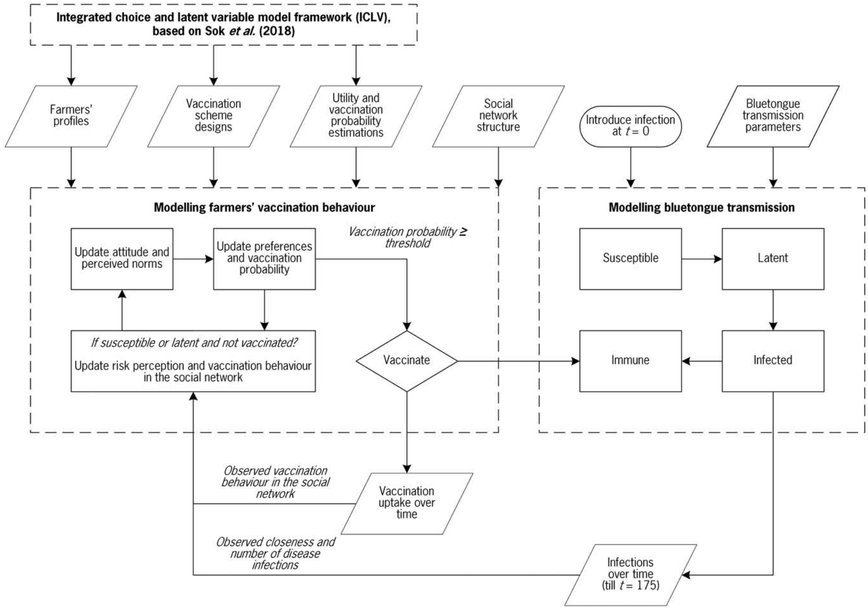

Fig. 1. Overview of the information flow between and within sub-models of farmers' vaccination behaviour and disease epidemiology.

(175 days), in which the epidemic starts with a set of initially infected farms at day 0.

2.2. Bluetongue transmission

The epidemiology of bluetongue is described with a spatial explicit discrete time susceptible-latent-infectious-recovered (SLIR) model. The farm is the epidemiological unit, thus individual animals are not modelled. In the *SLIR* model, each farm can be in one of the four states: susceptible (S), latent (L), infectious (I) or recovered or immune (R). Susceptible farms can become latently infected, then infectious to other farms and finally recover and become immune. Transmission between two farms is a stochastic process, the probability of which is determined by the Euclidean distance between farms (Boender *et al.*, 2007; de Koeijer *et al.*, 2011). If a farmer applies vaccination, his or her farm is considered to be immune. This means that, at the farm-level, we assume the vaccination to be 100 per cent efficacious. A more elaborated description of the modelling of bluetongue transmission is found in Appendix I in supplementary data at *ERAE* online.

2.3. Social network

A social network structure is imposed that connects farmers through social circles (Hamill and Gilbert, 2015). This simple structure fits with sociological observations of real social networks, such as low density, high clustering and communities. Using the idea of social circles, Hamill and Gilbert (2009) indicate that the social distance, d_{nm}, between any pair of agents n and m reflects the strength of the connection between them. We assume here that geographical distance alone determines social distance.

Specifically, we apply a two-reach network model (Hamill and Gilbert, 2009). The total number of farms N is randomly divided up into two groups, major (N_{major}) and minor (N_{minor}); the first group has a small radius (r_{small}) social network, and the second has a small radius and also a large radius (r_{large}) social network. N_{minor} represents a group of farmers with a more extensive social network, e.g. with connections through a study group. Each pair of farmers, no matter the group identity, is socially connected if $d_{nm} \leq r_{\text{small}}$. Additional connections are formed in N_{minor} if $r_{\text{small}} < d_{nm} \leq r_{\text{large}}$. This approach results in a so-called fat-tailed distribution of connectivity, i.e. some farmers have large networks. All input parameter values chosen as default values are given in Appendix II, Table A-1 in supplementary data at *ERAE* online.

Farmers who vaccinate their herd exert social pressure on peers in their network to also vaccinate to the extent of the strength of the node. This strength of the node is based on the similarity between two farmers. Peers with great similarity are assumed to exert more social pressure on each other (e.g. Weisbuch *et al.*, 2002). For each connection between farmer n and farmer m in the social network, a measure of similarity (f_{nm}) between the farmers is calculated by taking the inverse Euclidean distance between them in a four-dimensional space defined over herd size, milk production, land and age.

2.4. Farmer profiles and 'update' function

Farmers in the ABM are assigned randomly to a farmer profile, which is one of the 211 observations in our data set of farm and farmer characteristics and the three factor scores for attitude, injunctive and descriptive norms (Sok *et al.*, 2018). As a result, each farmer profile is assigned to multiple agents.

The results of the multinomial logit model with alternative-specific regressors of Sok *et al.* (2018), was used to assign farmers with an 'update' function for different vaccination scheme designs (see Tables 1 and 2). Farmer's probability of vaccination (P_{int}) is given as:

$$P_{int} = \frac{1}{1 + \exp\left(-V_{int}\right)}, \tag{1}$$

where

$$V_{int} = \beta_s \cdot X_{si} + \left(\sum\nolimits_p \alpha_{sp} \cdot z_{pn} + \sum\nolimits_l \tau_{sl} \cdot \eta_{lnt}\right) \cdot X_{si} \tag{2}$$

where V_{int} is the utility derived from vaccination scheme design i for farmer

Table 2. Selected levels of attributes and expected vaccination uptake level for each of the five vaccination schemes

	Strategy focus	*Change information dissemination*		*More financial compensation*
Scheme number →	1	2	3	4
Treatment →	Control	"Communication via vets"	"More confidence"	"Increase subsidy level"
Vaccination scheme attributes				
Probability of adverse vaccine effects	Small	Small	**Negligible**	Small
Government communication	Leaflet	**Veterinarian**	**Veterinarian**	Leaflet
Government subsidy	10%	10%	10%	**60%**
Vaccination costs per cow	8 euro	8 euro	8 euro	8 euro
Probability of herd infection	Nil	Nil	Nil	Nil
Vaccination probability distribution, based on the initial ICLV model estimations (Sok et al., 2018)				
Average	0.48	0.53	0.61	0.65
Min	0.01	0.00	0.01	0.02
25th percentile	0.24	0.26	0.38	0.50
Median	0.50	0.58	0.69	0.69
75th percentile	0.70	0.78	0.86	0.85
Max	0.96	0.98	0.99	0.98

profile n at time t; X_{si} attributes set to selected level s of vaccination scheme design i; β_s marginal utilities of a farmer when attributes are set to selected level s; z_{pn} values of farm or farmer characteristic p; α_{sp} interaction effects between z_{pn} and X_{si}; η_{lnt} factor scores on social-psychological construct l at time t and τ_{sl} interaction effects between η_{lnt} and X_{si}. The subscript t only appears in the factor scores of attitude, injunctive norm and descriptive norm. Using the bluetongue transmission model (Section 2.1) and the social network structure (Section 2.2), we explain in the next section how two heuristics update these constructs, and these constructs, in turn, update the vaccination probability (see Figure 1).

As soon as P_{int} exceeds a calibrated constant threshold value T, the farmer decides (D_{int}) to vaccinate the livestock on their farm:

$$D_{int} = \begin{cases} 1, P_{int} \geq T, \\ 0, P_{int} < T. \end{cases} \tag{3}$$

Since equation (2) includes interaction effects of farm and farmer characteristics and social-psychological constructs, each farmer profile for a given vaccination scheme design begins the simulation (in $t = 0$) with a unique P_{int}. The estimated β_s, α_{sp} and τ_{sl} values are given in Table A-2 in supplementary data at *ERAE* online.

2.5. Updating the vaccination probability

We see the vaccination decision as a short-term decision problem that is separate from livestock disease management and decision making in general. Farm and farmer characteristics are fixed through time. Attitude, injunctive and descriptive norms, however, are belief-based and adjusted through daily occurrences (Fishbein and Ajzen, 2010). These constructs are used in the decision-making process to update the vaccination probabilities (see Figure 1). Two simple heuristics are used to update attitude, injunctive norm and descriptive norm: perceived risk and perceived social pressure.

Risk perception in the literature is understood as an intuitive risk judgement based on limited and uncertain information (Slovic, 1987). Farmers in the ABM do not act as economically rational decision makers fully aware of the epidemiological state of all farms at a certain time. Each farmer observes the number and closeness of infected farms and constructs a risk perception (q_{nt}) as follows:

$$q_{nt} = \left(\frac{N_t^I}{N}\right)^{\frac{\min_{m \in I} d_{nmt}}{d_{\max}}}, \tag{4}$$

where N_t^I is the number of infected farms I, d_{nmt} is the distance between farm n and the closest infected farm and $d_{\max}$ is the maximum possible distance between two farms in the simulation.

Attitude and risk perception have been linked to each other (e.g. Sjöberg, 2000). Farmers who are strongly in favour of herd vaccination perceive the risk of disease infection most likely as higher, and vice versa (Sok *et al.*, 2016). The attitude measurements we collected can hold cognitive (instrumental) but also affective (experiential) considerations (Ajzen, 2001). As such, we consider the importance of experiences, emotions and affect in perceptions of risk (Slovic *et al.*, 2004; Slovic *et al.*, 2007). Attitude functions as a mediator between risk perception and the farmer's vaccination probability; it is updated during the simulation as:

$$\eta_{\mathrm{Ant}} = \eta_{An}^0 \cdot (1 + q_{nt}), \tag{5}$$

where η_{An}^0 is the initial attitude score at time t = 0, which is normalised to a value between 0 and 1. The effect of risk perception is therefore proportional to the initial attitude score.

In the ABM, perceived social pressure is modelled using the number of vaccinated farms in the social network. This way of modelling is inspired by the threshold model (Granovetter, 1978), in which the threshold is the proportion of neighbours that is necessary to convince the agent to act. Each farmer perceives social pressure (h_{nt}) to vaccinate as a function of the number of other farmers in the social network who have already vaccinated (g_{nmt}) and the similarity of their own farm and self to these peers (f_{nm}):

$$h_{nt} = \left(\frac{\sum_m f_{nm} \cdot g_{nmt}}{\sum_m g_{nmt}}\right)^{\gamma}. \tag{6}$$

The network size sensitivity (γ) parameter in the power term is a value between 0 and 1. As gamma decreases from 1 to 0, more weight is placed on the first farmer in the network who vaccinates and less weight to the peer who vaccinates last (i.e. most recently), especially in smaller social networks.

Injunctive norms are farmers' perceptions of what referents of influence think should be done (i.e. vaccinate or not). Referents of influence are: family members, the veterinarian, peers and leaders, and the buyer (Sok *et al.*, 2015). Descriptive norms are mainly perceived behaviour of peers. The ABM only models peer social pressures. Both types of social norm are updated during the simulation as:

$$\eta_{DNnt} = \eta^0_{DNn} \cdot (1 + h_{nt}), \tag{7}$$

$$\eta_{INnt} = \eta^0_{INn} \cdot (1 + h_{nt}), \tag{8}$$

where η^0_{DNn} and η^0_{INn} are the initial descriptive norm score and initial injunctive norm at time $t = 0$, respectively, which both are normalised to a value between 0 and 1.

2.6. Application

We used the ABM presented in Section 2 to simulate vaccination scheme design and test their uptake. Full model details are found in an Overview, Design concepts and Details + Decision (ODD + D) protocol, with more details on, e.g. model process implementation, calibration and sensitivity analysis (Müller *et al.*, 2013). The ODD + D protocol and the model code are accessible via OpenABM (Fischer, 2019)[3].

Table 2 presents four vaccination scheme designs, with selected levels for each attribute and descriptive statistics of the vaccination probability distribution that we calculated using the multinomial logit model (Sok *et al.*, 2018). The designs tested differ in five attributes including 'probability of adverse vaccine effects' (captures farmers' trust and confidence in the vaccination approach), how information is disseminated and in the level of subsidy. Vaccination costs per cow were kept constant across the simulations.

The schemes each are simulated 50 times, using fixed random 'seeds'. The latter is a model run with a specific set of initial conditions. These initial conditions are the farm's location and the farmer's profile. The location, in turn, determines the probability of infection between an infected and a susceptible farm and the shape and size of the social network (see Sections 2.1 and 2.3). It is also determined in the model initialisation at which a farm's bluetongue disease transmission starts (see Appendix I).

The first design is the 'control' scheme and is used to calibrate the threshold probability value[4], perform a series of verification[5] steps and sensitivity

3 Data underlying the farmer profiles are available upon request.

4 We first used the multinomial logit model in Sok *et al.* (2018) to calculate the average vaccination probability under the base scheme (48 per cent). We then ran a series of simulations varying the network sensitivity parameter (γ) of equation (6) and the threshold probability value T (see Figure 1). We set γ at 0.25 and T at 0.978 to obtain an average uptake of about 48 per cent.

5 Specific verification steps we completed included: checking the Netlogo code, diagnosing intermediate outputs (e.g. updating of the social-psychological constructs), observing the simulation

analyses of social network and disease transmission parameters, and validate[6] the model. We then consider three 'treatment' simulations that are based on two strategies for improving the uptake compared to the control scheme. The first and second treatments change the way information is disseminated and the third treatment provides more financial compensation to farmers. Both strategies are expected to improve vaccination uptake compared to the control: financial compensation, however, is expected to be a more effective instrument, given the averages of the calculated vaccination probability distributions.

Animal health authorities do not observe farmers' motives. The strategies mentioned above make use of insights from social psychology and behavioural economics, i.e. how to use motivational mechanisms such as social pressure in policy designs that rest on voluntary participation. It has been shown that different motivational mechanisms underlie the effectiveness of informational or incentive-based policy instruments (Sok *et al.*, 2018). The functioning of these mechanisms is described below.

The ICLV model estimations indicated that farmers' prefer receiving information from more informal sources (veterinarian) rather than via formal sources (leaflet), and this preference is *positively* correlated with a pro-vaccination attitude (Sok *et al.*, 2018). Schemes 2 and 3 change the way information is disseminated in the ABM from leaflets to veterinarians. The motivational mechanism that positively affects attitude and behaviour is the change of the source and message characteristics of the risk communication strategy (Petty and Cacioppo, 1996; Blackstock *et al.*, 2010).

Veterinarians are commonly perceived as a highly trusted information source in The Netherlands (Sok *et al.*, 2015). The ICLV model estimations indicated that the probability to vaccinate increased with more trust and confidence in the vaccination approach. Farmers' preference for negligible adverse vaccine effects is weakly *positively* correlated with stronger descriptive norms (Sok *et al.*, 2018). These findings reveal another motivational mechanism: if farmers perceive peers in their social network vaccinating presumably without experiencing adverse effects, they become more likely to vaccinate. The design of vaccination scheme 3 builds on the idea that involving veterinarians in risk communication also leads to more perceived trust and confidence.

We test with scheme 4 how increasing financial compensation affects the vaccination uptake: the level of subsidy is increased from 10 to 60 per cent of the total vaccination costs. The ICLV model estimations, however, indicated that farmers' preference for receiving more subsidy is weakly *negatively* correlated with stronger injunctive norms (Sok *et al.*, 2018). The underlying motivational mechanism we model is that subsidy and social pressures are

one at a time and corner-testing with extreme values (e.g. setting the infectious period at zero, which should lead to no additional infected farms).

6 Validation was done as follows. Two output variables were defined: the percentage of infected farms, and the percentage of vaccinated (immune) farms (the uptake). First, 50 simulations were run in which no vaccination scheme was offered. Then, another 50 simulations were run with a base vaccination scheme design offered to farmers at t = 56 (approximately 2 months). Results were compared with other estimations of the vaccine uptake reported in the literature.

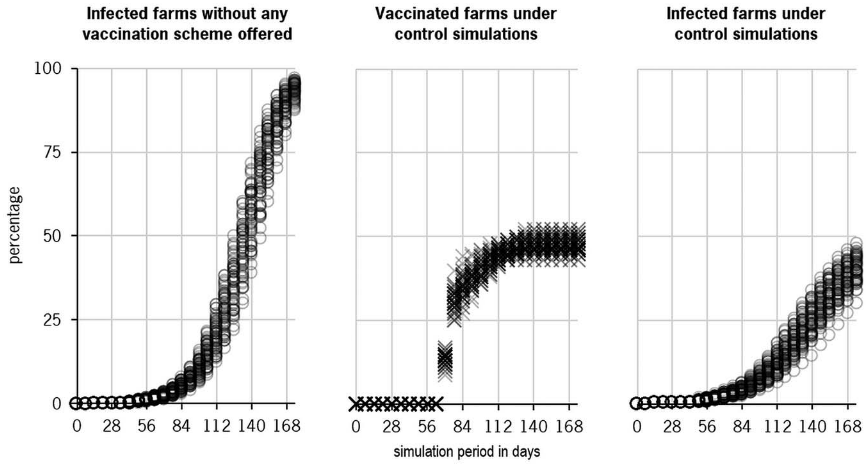

Fig. 2. Validation results depicting the time trajectories of simulations with and without vaccination offered, showing how vaccination reduces the number of bluetongue infected farms. One circle or cross at each time moment corresponds to one simulation.

both extrinsic motivating factors; they act as substitutes. More financial compensation increases the likelihood that a farmer vaccinates the herd, but this effect is partially offset when perceived social pressures increase. Increasing the subsidy level crowds-out motivation to vaccinate from perceptions of what referents of influence think should be done.

3. Results

We begin by showing the results of a series of simulations aimed at validating the ABM with respect to the epidemiology. The left panel in Figure 2 shows the percentage of farms infected if no vaccination scheme is offered. The comparison of the simulation results with the actual bluetongue serotype 8 epidemic from 2006 to 2009 in The Netherlands shows a reasonable resemblance to the epidemiology. Velthuis *et al.* (2010) estimated the percentage of farms infected in The Netherlands (both cattle and sheep) in 2007 at 82.7–99.9 per cent, depending on the region (North, Middle or South). The percentages of farms infected in our simulated epidemics without any vaccination scheme offered are in line with these percentages. Differences in the severity of disease (the prevalence of subclinical versus clinical manifestations) were not taken into account.

The middle- and right-hand panels in Figure 2 show the percentage of farms vaccinated and infected, respectively, under control simulations (scheme 1). Approximately 50 per cent of farms become immune through vaccination. The government introduces the vaccination scheme after 56 days (approximately 2 months). Most farmers who intend to vaccinate their herds do so in the

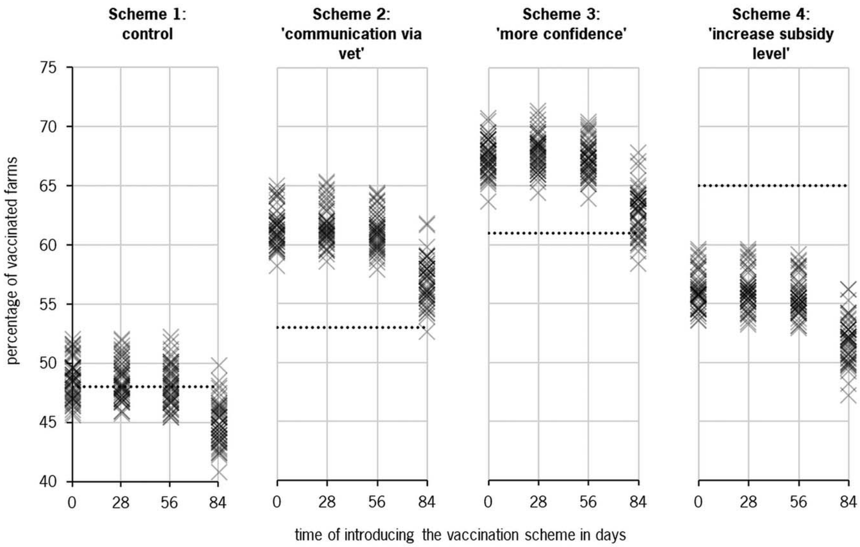

Fig. 3. Farmers' vaccination uptake under the four vaccination scheme designs. One cross corresponds to the result of one simulation with a different model initialisation, measured at the end of the simulation period. The horizontal lines are the expected ex-ante average uptake levels based on initial ICLV model estimations.

subsequent three months, resulting in an uptake of about 50 per cent. Thereafter, no more farmers vaccinate whilst the percentage infected farms is still growing.

Next, Figure 3 shows the simulation results for the four alternative vaccination scheme designs we are interested in (see Section 2.3). The depicted uptake under the control simulations, in which the scheme is introduced after 56 days, corresponds to the uptake in the middle panel in Figure 2 at the end of the simulated period. These results indicate that starting vaccination immediately in the vector season, or after one ($t = 28$) or two months ($t = 56$), does not lead to different uptake levels for different schemes. The uptake starts to decrease when vaccination is introduced after three months ($t = 84$). Farmers who were willing to vaccinate at that time already observed that their herd is infected.

The horizontal lines in Figure 3 are the expected *ex ante* average vaccination uptake levels that were reported in Table 2. The uptake under control simulations is, on average, equal to the expected uptake. As explained before, this simulation was done for validation purposes and to allow comparison of the ICLV model predictions with the ABM simulations. Differences in predicted versus simulated uptake under treatment simulations are then the result of the model components we added, including the information diffusion processes of disease risk information and of vaccination behaviour of others.

Vaccination uptake under all treatment simulations is higher than the uptake under the control simulations, just as inferred from the initial ICLV model estimations. Both strategies – changing the way information is disseminated and providing more financial compensation – lead to more farmers vaccinating their herd and less farms being infected with bluetongue. Schemes 2 and 3, however, perform better than expected, whilst scheme 4 performs worse.

The effects we observe in Figure 3 cannot be attributed to input parameter value settings. Results of sensitivity analyses performed are given in Tables A-3 and A-4 in supplementary data at *ERAE* online. They show that changing values of disease transmission input variables or social network variables hardly influence vaccination uptake (percentage of vaccinated farms). There is one input parameter value that substantially affects the uptake: the small radius (r_{small}) of the social network structure (see Section 2.3). The default small radius was set at 2 km. Changing it to 1 km reduces the uptake under control simulations with, on average, more than 10 per cent and under treatment simulations with, on average, about 5 per cent. Changing it to 3 km did not significantly affect uptake levels.

We compared the percentage of vaccinated (immune) farms with other estimations of the vaccination uptake reported in the literature. As explained before, the 48 per cent uptake was calibrated to be in line with the ICLV model results from Sok *et al.* (2018), which was based on a survey held in 2015 amongst 1,500 Dutch dairy farmers. From a survey undertaken in 2009, the level of participation in 2008 in the middle of an epidemic amongst cattle farmers was estimated at 71 per cent with many farmers, whose herds had become infected in 2007 deciding still to vaccinate. In 2009, the estimated uptake, based on either actual participation or stated intention, dropped to 57 per cent (Elbers *et al.*, 2010). From a survey undertaken in 2014, 6–7 years after the epidemic, the lower limit of participation was estimated at 40 per cent of the total population of farmers (Sok *et al.*, 2016). In the ABM simulations, farmers whose herds became infectious never vaccinated; it was assumed farmers know that once their herd has become naturally infected, vaccination is not needed afterwards to become immune. All in all, we think that the simulated uptakes are in line with these estimations of the real uptake.

We continue by elaborating on the mechanisms of vaccination uptake for the different schemes. Figure 4 illustrates the functioning of the motivational mechanisms described in Section 2.3 as reflected in the marginal utility for different vaccination scheme attributes. Average marginal utilities for government information, for adverse vaccine effects and for government subsidy were calculated[7]. Figure 5 shows incremental vaccine uptake by farmers under schemes 2, 3 and 4 (treatment simulations) relative to scheme 1 (control simulations). Table 3 gives the summary statistics of the retrieved profiles

7 We retrieved after each month (28 days) the average marginal utility for different attributes in the ABM. Agents stopped updating these values in the ABM when their farm became infected or when they decided to vaccinate. Using ICLV model estimations (Appendix II, Table A-2 in supplementary data at *ERAE* online), average marginal utility at time t for a certain attribute X (e.g. government information) with selected level s (e.g. via veterinarian) was calculated as: $\sum_n \frac{-0.54+1.10\cdot\eta^0_{An}\cdot(1+q_{nt})}{N}$ (government information via leaflets).

Table 3 Mean values of farmer profiles (farm and farmer characteristics and initial attitude and perceived norm scores) of the whole sample, and under control and treatment simulations (retrieved). Standard deviations are in brackets.

Treatment		Scheme 1: Control	Scheme 2: 'Communication via vets'	Scheme 3: 'More confidence'	Scheme 4: 'Increase subsidy level'	
Segment (Figure 5)	Whole sample	White	Grey	Black	Shaded	Not vaccinated
No. of farmer profiles	211	100	32	11	22	62
Herd size	104	97	103	158	108	108
	(48)	(37)	(43)	(79)	(41)	(55)
Milk production	8,529	8,676	8,743	8,100	8,831	8,220
	(1,118)	(993)	(892)	(986)	(993)	(1,356)
Pasture land	47	41	40	68	40	47
	(33)	(17)	(16)	(27)	(14)	(52)
Export of heifer	0.26	0.39	0.13	0.27	0.09	0.15
Age	48	48	46	38	45	48
	(10)	(10)	(9)	(8)	(10)	(11)
Higher education	0.27	0.31	0.25	0.18	0.32	0.24
Attitude (initial score)	4.5	5.6	4.7	4.0	4.8	2.9
	(1.5)	(0.9)	(0.6)	(0.4)	(0.7)	(1.4)
Injunctive norm (initial)	3.6	4.6	3.6	4.4	3.6	2.0
	(1.7)	(1.4)	(1.4)	(1.0)	(1.5)	(1.0)
Descriptive norm (initial)	3.9	4.6	3.9	4.1	3.7	2.7
	(1.4)	(1.0)	(1.4)	(0.9)	(1.2)	(1.2)

of those farmers that vaccinated under each scheme[8]. Within these segments, mean and standard deviation values of the farm and farmer characteristics and the initial scores (at $t = 0$) on attitude, injunctive and descriptive norms can be compared with each other and with statistics of the whole sample.

Almost half of the farmers vaccinate under scheme 1. Compared to the whole sample statistics, these farmers score higher on attitude and injunctive norms (see Table 3). This segment contains on average more farms with export activities. Both observations indicate that many farmers who vaccinate under control simulations are self-motivated – either intrinsically or extrinsically – and need no further motivation.

Vaccination schemes 2 and 3 reach an uptake of more than 60 per cent. The incremental uptake of scheme 2 relative to scheme 1 is about 15 per cent and is the result of changing source and message characteristics from leaflets to veterinarians (see Figure 5). Characteristics of farmers (and their farm) that start vaccinating under scheme 2 are comparable to those of the whole sample. Over the simulation period, utility of information starts to slightly decline when leaflets are used because of increasing risk perceptions and updated attitude scores. As farmers become increasingly aware of disease risk, they search for trusted information sources. When changing to veterinarians, utility for information quadruples over time (Figure 4, left panel).

8 There were more farmers than farmer profiles in the ABM (i.e. each farmer profile was assigned to multiple farmers). We used a cut-off value for the number of farms vaccinated to select the farmer profiles.

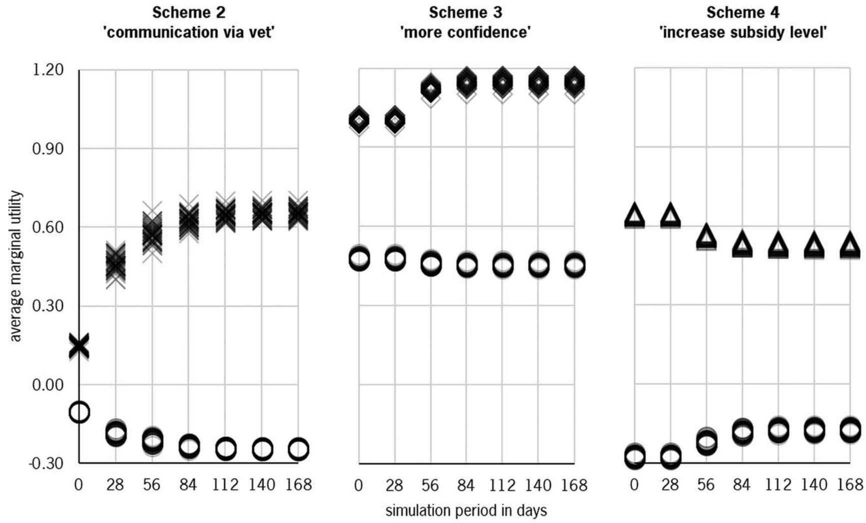

Fig. 4. The functioning of motivational mechanisms as reflected in the change in average marginal utility for different vaccination scheme attributes. Crosses denote utility for communication via vets, diamonds denote utility for adverse vaccine effects being *negligible*, triangles denote utility for 60 per cent subsidy. Circles denote utility of the corresponding attribute level under control simulations (leaflet, small, 10 per cent in scheme 1).

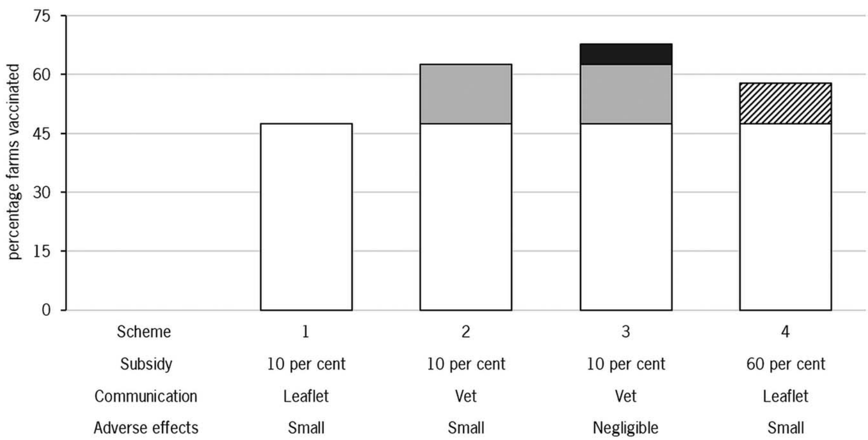

Fig. 5. Incremental vaccine uptake of farmers under different schemes relative to the base scheme. The parts in grey are the increment when providing information through the veterinarian, in black the increment when perceived adverse effects are negligible, shaded when more compensation is provided.

Farmers with a favourable attitude quickly reach a vaccination probability that exceeds the threshold probability at the time the animal health authorities introduce the vaccination scheme. These pro-vaccination farmers positively impact the likelihood of vaccination of other farmers as well through social pressures.

The incremental uptake of about 5 per cent for scheme 3 relative to scheme 2 is the result of more perceived trust and confidence in the vaccination approach. At the time when the animal health authorities start to offer a vaccination, a large group of farmers, being self-motivated or motivated by information via veterinarians, decides to participate. A smaller group of farmers, being more concerned about possible adverse vaccine effects, observe that their peers vaccinate without experiencing negative adverse vaccine effects in their herd, and become more convinced to participate as well. This is reflected in the utility increase after vaccination introduction (Figure 4, middle panel). The behaviour of farmers who start vaccinating under scheme 3 is more driven by social norms as suggested by the higher scores on both injunctive and descriptive norms. This segment of farmers tends to be less educated, younger and their farm is operated less intensively, but we should be careful here because of the small number of farmers in this segment (see Table 3).

Vaccination scheme 4 follows a strategy of providing more financial compensation, and reaches an incremental uptake of about 10 per cent relative to scheme 1. Average utility for subsidy increases substantially. Figure 4, right panel shows that utility of subsidy starts to decline at the time the animal health authorities start to offer vaccination and social pressures build up expectations to vaccinate. It illustrates a small crowding-out effect: farmers' increasing motivation in response to external social pressures starts to crowd-out the financial incentive that was provided with a higher subsidy level. Comparing the different counterfactuals, we further observe that farmers who vaccinate under scheme 4 also vaccinate under either scheme 2 or 3. This suggests the two motivational mechanisms that can be activated by a well-developed risk communication strategy are equally or more effective in increasing vaccination uptake than the financial incentive of providing more compensation of the costs of herd vaccination.

4. Discussion and conclusions

Our study confirms that ABMs can provide valuable insights into complex interactions between variables over time and can capture remarkably subtle feedback effects that are easily missed by comparative static models (Nolan *et al.*, 2009; Schreinemachers *et al.*, 2009). Specific scheme designs improve the vaccine uptake by farmers at the start of a livestock disease epidemic, compared to a base scheme in which there is minimal communication and subsidy. The results suggest that motivational mechanisms activated by a well-designed risk communication strategy are equally or more effective in increasing vaccination uptake than providing more financial compensation. The high uptake of vaccination in response to schemes that focus on information dissemination can be explained as the result of an emergent effect (see, e.g. Epstein, 1999). The analyses show that attitudes in combination with descriptive norms play a large role in this respect. The 'hidden' policy instrument *social pressures* serves as a 'catalyst', making use of the local interactions between highly self-motivated farmers and farmers, whose behaviour is driven more by social norms, and this catalyst boosts the uptake up to a level that is not suggested by the logit model in Sok *et al.* (2018). These findings highlight the strength of agent-based modelling with its ability to define heterogeneity and interaction processes at the individual level to study population-level dynamics.

Results also highlight the complementary nature of different policy instruments. Informational instruments only work if farmers are receptive to the information, which we measured by their attitude towards vaccination. Trust in the sender of information and confidence in the disease control approach further determines whether farmers are willing to vaccinate their animals. Their willingness is based on a heterogeneous set of motives that are economic, intrinsic and social in nature. The signalling function of financial compensation probably is more important than the cost reduction itself in the context of livestock disease control. Following motivation crowding theory, subsidies can negatively affect one's sense of autonomy (not the capacity) over the behaviour, resulting in resistance to (rather than compliance with) the policy. How informational and financial-incentive based policy instruments could strengthen each other remains unanswered in our research and is an important question for follow-up research for which an experimental approach might work best.

A weakness of our modelling is the oversimplification of social interaction processes. In a robustness analysis, we varied the input parameter values in the model and found the social circles network did not change much of the effectiveness of most vaccination scheme designs that are tested, except the small radius parameter for the base scheme. Farmers in the ABM feel more social pressure to vaccinate if they observe that others in their social network vaccinated. We captured this by the similarity between two interacting farmers in terms of the farm characteristics – herd size, milk production and land as well as farmer characteristics. An advancement in the modelling of social interaction influences would have been the use of the relative agreement influence model (Deffuant, Huet and Amblard, 2005), which also takes into account the role of opinion leaders; farmers can persuade each other to adopt an innovation, given diverging opinions about the innovation, depending on the level of uncertainty, conviction and openness to the opinion of others.

We also highlight a need for a better understanding of how information diffusion processes really work. In our ABM, information about both disease risk and about vaccination behaviour of others diffuses through networks of farmers. These two diffusion processes impact farmers' collective behaviour and the coupling can have positive or negative effects (Bauch and Galvani, 2013). We find that the speed with these diffusion processes work differ in our application. The presence of a latency period of 14 days in the disease transmission component results in a slower diffusion of disease information used by farmers to update their risk perception compared to the spread of vaccination information that they use to update their perceived social pressure. However, varying the disease transmission input parameter values did not truly affect the percentage of vaccinated farms, whereas it did affect the percentage of infected farms (Appendix II, Table A-3 in supplementary data at *ERAE* online). The 'hard epidemiological facts' itself do not drive farmers' behaviour; it is rather perceptions of these facts that drive decision making (Funk, Salathé and Jansen, 2010; Hidano *et al.*, 2018).

How would a collective of farmers in a situation of a disease epidemic respond to a voluntary vaccination policy? The most effective voluntary vaccination scheme design as a reactive measure to an epidemic that is in its early stages aims at serving information needs of farmers that, in the presence of a high level of perceived trust and confidence, induces others in the social network to vaccinate. The ABM simulations for the case of bluetongue disease amongst dairy herds in The Netherlands suggest, however, that about 30 per cent of farmers cannot be motivated to voluntarily vaccinate their herds, which makes herd immunity unlikely. This may be a reason to consider mandatory-type policies such as targeted or risk-based vaccination strategies. Our research does not give insights into the cost effectiveness of, for example, mandatory versus voluntary vaccination approaches or informational versus financial-incentive based policy instruments. Our research does, however, show the importance of social networks in the context of voluntary vaccination programmes. The choice between voluntary or mandatory programmes further depends on the epidemiological situation, such as previous epidemics. Low vaccination uptake in combination with many farms that have already become immunised via natural infection may be enough to control the next epidemic. In this study, we only addressed an epidemic during the year after first introduction. In subsequent years, bluetongue can become an endemic disease in affected areas. The dynamics of both farmers' collective behaviour and also of the disease epidemiology might alter in such a situation. Scenarios of this kind can be further investigated with our model.

In conclusion, to increase voluntary vaccination uptake by a collective of farmers, policy designs need to account for differences amongst farmers in their economic, intrinsic and social motives to vaccinate cattle. Risk communication instruments can (first) target the highly motivated farmers. The more trust and confidence there subsequently is in the disease control approach, the more farmers will be influenced by social pressures to vaccinate. How informational and financial-incentive based instruments could strengthen each other in livestock disease control policies needs further research.

Supplementary data

Supplementary data are available at *ERAE* online.

Funding

This research was funded by the Ministry of Economic Affairs (Netherlands Food and Consumer Product Safety Authority) of The Netherlands via EMIDA

ERA-NET 'Coordination of European Research on Emerging and Major Infectious Diseases of Livestock' (funded by the European Commission's Seventh Framework Programme, Project No. 219235). We thank the reviewers and the editor for their time and effort in providing comments.

References

Ajzen, I. (2001). Nature and operation of attitudes. *Annual Review of Psychology* 52: 27–58.

An, L. (2012). Modeling human decisions in coupled human and natural systems: review of agent-based models. *Ecological Modelling* 229: 25–36.

Bauch, C. T. and Galvani, A. P. (2013). Social factors in epidemiology. *Science* 342: 47–49.

Ben-Akiva, M., de Palma, A., McFadden, D. *et al.* (2012). Process and context in choice models. *Marketing Letters* 23: 439–456.

Benartzi, S., Beshears, J., Milkman, K. L. *et al.* (2017). Should governments invest more in nudging? *Psychological Science* 28: 1041–1055.

Blackstock, K. L., Ingram, J., Burton, R. *et al.* (2010). Understanding and influencing behaviour change by farmers to improve water quality. *Science of The Total Environment* 408: 5631–5638.

Boender, G. J., Hagenaars, T. J., Bouma, A. *et al.* (2007). Risk maps for the spread of highly pathogenic avian influenza in poultry. *PLoS Computational Biology* 3: e71.

Bonabeau, E. (2002). Agent-based modeling: methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America* 99: 7280–7287.

Bowles, S. and Polanía-Reyes, S. (2012). Economic incentives and social preferences: substitutes or complements? *Journal of Economic Literature* 50: 368–425.

Bruch, E. and Atwell, J. (2015). Agent-based models in empirical social research. *Sociological Methods & Research* 44: 186–221.

Chhatwal, J. and He, T. (2015). Economic evaluations with agent-based modelling: an introduction. *Pharmacoeconomics* 33: 423–433.

Czap, N. V., Czap, H. J., Lynne, G. D. *et al.* (2015). Walk in my shoes: nudging for empathy conservation. *Ecological Economics* 118: 147–158.

de Koeijer, A., Boender, G., Nodelijk, G. *et al.* (2011). Quantitative analysis of transmission parameters for bluetongue virus serotype 8 in Western Europe in 2006. *Veterinary Rese* 42: 53.

Deci, E. L., Koestner, R. and Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological Bulletin* 125: 627–668.

Deffuant, G., Huet, S. and Amblard, F. (2005). An individual-based model of innovation diffusion mixing social value and individual benefit. *American Journal of Sociology* 110: 1041–1069.

Dessart, F. J., Barreiro-Hurlé, J. and van Bavel, R. (2019). Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics* 46(3): 417–471.

Eisenhardt, K. M. (1989). Agency theory: an assessment and review. *The Academy of Management Review* 14: 57–74.

Elbers, A. R., de Koeijer, A. A., Scolamacchia, F. *et al.* (2010). Questionnaire survey about the motives of commercial livestock farmers and hobby holders to vaccinate their animals against bluetongue virus serotype 8 in 2008-2009 in the Netherlands. *Vaccine* 28: 2473–2481.

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity* 4: 41–60.
Fischer, E. (2019). Model for decision making of farmers to vaccinate against bluetongue virus (Version 1.0.0). CoMSES Computational Model Library. Retrieved from: https://www.comses.net/codebases/e424cfb3-b370-42fe-bc9a-8126ce5bce6c/releases/1.0.0/.
Fishbein, M. and Ajzen, I. (2010). *Predicting and Changing Behavior: The Reasoned Action Approach*. New York: Psychology Press.
Frey, B. S. and Jegen, R. (2001). Motivation crowding theory. *Journal of Economic Surveys* 15: 589–611.
Funk, S., Salathé, M. and Jansen, V. A. A. (2010). Modelling the influence of human behaviour on the spread of infectious diseases: a review. *Journal of The Royal Society Interface* 7: 1247–1256.
Gilbert, N. (2008). *Agent-Based Models*. London: Sage Publications.
Gramig, B. M., Horan, R. D. and Wolf, C. A. (2009). Livestock disease indemnity design when moral hazard is followed by adverse selection. *American Journal of Agricultural Economics* 91: 627–641.
Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology* 83: 1420–1443.
Greiner, R. and Gregg, D. (2011). Farmers' intrinsic motivations, barriers to the adoption of conservation practices and effectiveness of policy instruments: empirical evidence from northern Australia. *Land Use Policy* 28: 257–265.
Groeneveld, J., Müller, B., Buchmann, C. M. *et al.* (2017). Theoretical foundations of human decision-making in agent-based land use models: a review. *Environmental Modelling & Software* 87: 39–48.
Hamill, L. and Gilbert, N. (2009). Social circles: a simple structure for agent-bahsed social network models. *Journal of Artificial Societies and Social Simulation* 12: 3.
Hamill, L. and Gilbert, N. (2015). Social demand. In *Agent-Based Modelling in Economics*. New York: John Wiley & Sons, Ltd, 53–79.
Hennessy, D. A. and Wolf, C. A. (2015). Asymmetric information, externalities and incentives in animal disease prevention and control. *Journal of Agricultural Economics*. 69: 226–42.
Hensher, D. A., Rose, J. M. and Greene, W. H. (2005). *Applied Choice Analysis: A Primer*. Cambridge: Cambridge University Press.
Hertwig, R. and Grüne-Yanoff, T. (2017). Nudging and boosting: steering or empowering good decisions. *Perspectives on Psychological Science* 12: 973–986.
Hidano, A., Enticott, G., Christley, R. M. *et al.* (2018). Modeling dynamic human behavioral changes in animal disease models: challenges and opportunities for addressing bias. *Frontiers in Veterinary Science* 5: 1–14.
Huber, R., Bakker, M., Balmann, A. *et al.* (2018). Representation of decision-making in European agricultural agent-based models. *Agricultural Systems* 167: 143–160.
Klabunde, A. and Willekens, F. (2016). Decision-making in agent-based models of migration: state of the art and challenges. *European Journal of Population* 32: 73–97.
Kreps, D. M. C. (1997). Intrinsic motivation and extrinsic incentives. *The American Economic Review* 87: 359–364.
Kuhfuss, L., Préget, R., Thoyer, S. *et al.* (2015). Nudging farmers to enrol land into Agri-environmental schemes: the role of a collective bonus. *European Review of Agricultural Economics* 43: 609–636.
Müller, B., Bohn, F., Dreßler, G. *et al.* (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software* 48: 37–48.

Nolan, J., Parker, D., Van Kooten, G. C. *et al.* (2009). An overview of computational modeling in agricultural and resource economics. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 57: 417–429.

Pacilly, F. C. A., Hofstede, G. J., Lammerts van Bueren, E. T. *et al.* (2018). Simulating crop-disease interactions in agricultural landscapes to analyse the effectiveness of host resistance in disease control: the case of potato late blight. *Ecological Modelling* 378: 1–12.

Petty, R. E. and Cacioppo, J. T. (1996). *Attitudes and Persuasion: Classic and Contemporary Approaches*. New York: Westview Press.

Rabin, M. (1998). Psychology and economics. *Journal of Economic Literature* 36: 11–46.

Rode, J., Gómez-Baggethun, E. and Krause, T. (2015). Motivation crowding by economic incentives in conservation policy: a review of the empirical evidence. *Ecological Economics* 117: 270–282.

Schreinemachers, P., Berger, T., Sirijinda, A. *et al.* (2009). The diffusion of greenhouse agriculture in northern Thailand: combining econometrics and agent-based modeling. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 57: 513–536.

Sjöberg, L. (2000). Factors in risk perception. *Risk Analysis* 20: 1–12.

Slovic, P. (1987). Perception of risk. *Science* 236: 280–285.

Slovic, P., Finucane, M. L., Peters, E. *et al.* (2004). Risk as analysis and risk as feelings: some thoughts about affect, reason, risk, and rationality. *Risk Analysis* 24: 311–322.

Slovic, P., Finucane, M. L., Peters, E. *et al.* (2007). The affect heuristic. *European Journal of Operational Research* 177: 1333–1352.

Sok, J., Hogeveen, H., Elbers, A. R. W. *et al.* (2015). Farmers' beliefs and voluntary vaccination schemes: bluetongue in Dutch dairy cattle. *Food Policy* 57: 40–49.

Sok, J., Hogeveen, H., Elbers, A. R. W. *et al.* (2016). Perceived risk and personality traits explaining heterogeneity in Dutch dairy farmers' beliefs about vaccination against bluetongue. *Journal of Risk Research* 21: 562–578.

Sok, J., van der Lans, I. A., Hogeveen, H. *et al.* (2018). Farmers' preferences for bluetongue vaccination scheme attributes: an integrated choice and latent variable approach. *Journal of Agricultural Economics* 69: 537–560.

Velthuis, A. G., Saatkamp, H. W., Mourits, M. C. *et al.* (2010). Financial consequences of the Dutch bluetongue serotype 8 epidemics of 2006 and 2007. *Preventive Veterinary Medecine* 93: 294–304.

Walker, J. and Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences* 43: 303–343.

Weisbuch, G., Deffuant, G., Amblard, F. *et al.* (2002). Meet, discuss, and segregate! *Complexity* 7: 55–63.

Wilensky, U. (1999). *NetLogo*. http://ccl.northwestern.edu/netlogo/. Center for Connectede Learning and Computer-Based Modeling, Northwestern University. IL: Evanston.

Wilson, A. J. and Mellor, P. S. (2009). Bluetongue in Europe: past, present and future. *Philosophical Transactions of the Royal Society B: Biological Sciences* 364: 2669–2681.

Wiltshire, S. W. (2018). Using an agent-based model to evaluate the effect of producer specialization on the epidemiological resilience of livestock production networks. *PLoS ONE* 13: e0194013.