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CRISPR Rice vs conventional rice dilemma of a Chinese farmer*

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Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) technology for rice, which makes rice resistant to its two most destructive insect pests, is an alternative to insect-resistant genetically modified (GM) rice. We advance an economic framework to determine ex ante the planting share of CRISPR rice in China under uncertainty about pest severity and analyse its most significant factors. Using our baseline data and an assumption that yields of CRISPR rice are 10 per cent lower than conventional rice, we estimate the planting share of CRISPR rice to be 37.9 per cent. The mean of the annual benefit of growing CRISPR rice and conventional rice together over conventional rice alone is 2.32 billion US dollars.

Key words: China, CRISPR rice, Monte Carlo simulations, optimal planting share, uncertainty.

1. Introduction

Rice is a staple food for more than half the population in China, and the area dedicated to growing it amounts to 30 million hectares, accounting for 25 per cent of the total arable land in China (National Bureau of Statistics of China [NBSC], 2018). This vast area of agricultural land reflects the importance of rice in feeding not only the domestic population but also many people in the rest of the world. However, rice suffers from insect pests with annual losses in billions of United States (US) dollars (Lu et al., 2018). The response of many Chinese rice farmers has been a notorious overuse of pesticides, which have adverse effects on farmers' health and the environment (Damalas & Eleftherohorinos, 2011), with application rates of 57 per cent above recommended levels (Zhang et al., 2015). One solution to this pesticide overuse is insect-resistant rice.

Scientists expected much from insect-resistant genetically modified (GM) rice. The classic example is *Bacillus thuringiensis* (Bt) rice, which was

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developed in the 1990s and received biosafety certificates in 2009. However, for political reasons, its commercialisation in China has been postponed. To date, Bt rice is not grown in any country in the world (Jin et al., 2019), although it has been approved for imports and consumption by the US Food and Drug Administration (FDA) (2018).

Recent advances in genome editing using the CRISPR/Cas9 for rice technology (Lu et al., 2018) present an alternative to insect-resistant GM rice. Genome editing enables scientists to edit or modulate deoxyribonucleic acid (DNA) sequences at particular locations in the genome. CRISPR/Cas9 is short for Clustered Regularly Interspaced Short Palindromic Repeats and CRISPR-associated protein 9, which can be guided to specific locations within complex genomes (Hsu et al., 2014). In 2018, Chinese scientists developed CRISPR rice by suppressing the biosynthesis of serotonin (a neurotransmitter in mammals) induced by insect infestation in rice (Lu et al., 2018). This suppression confers resistance to planthoppers and stem borers, the two most destructive insect pests of rice (Chen et al., 2011). Compared to GM rice, CRISPR rice[1] has a higher chance of making it to market because it is indistinguishable from rice developed by traditional breeding techniques, such as hybrid and conventional breeding, because no new genes are added (Lu et al., 2018). In fact, a mutation producing a gene structure similar to that of CRISPR rice can also occur in nature (Carlin, 2011; Lu et al., 2018). Some countries, such as the United States, plan not to consider CRISPR rice a GM product at all (US Department of Agriculture [USDA], 2018), and it will thus not need to be labelled once commercialisation is permitted. In China, however, whether CRISPR products will be regulated as GM products is under discussion.

There is a growing literature on CRISPR rice strains with different traits. Apart from insect-resistant CRISPR rice (Lu et al., 2018) on which our study is based, Wang et al. (2016) developed CRISPR rice with enhanced blast resistance. Four genes known as regulators of grain number, panicle architecture, grain size and plant architecture have been targeted (Li et al., 2016). Sun et al. (2016) also developed herbicide-tolerant rice with CRISPR technology.

CRISPR technology can contribute to meeting increasing global demand for food and facing global environmental challenges by revolutionising plant breeding (Cao, 2018). It can arguably produce results identical to conventional methods in a much faster, less costly and more predictable manner (Cao, 2018). However, the nature-identical modifications blur the boundary between nature and technology, which calls for a rethinking of regulatory approaches regarding to preferences of consumers, food ethics and governance (Bartkowski et al., 2018). Therefore, China's regulation of CRISPR

[1] There are different types of CRISPR rice with different traits, such as herbicide-tolerant and blast-resistant. In this paper, however, 'CRISPR rice' specifically refers to the insect-resistant CRISPR rice developed by Lu et al. (2018).

rice is crucial to this highly contested and controversial societal issue with the potential to significantly affect the social welfare of various rice stakeholders.

Because the commercialisation of insect-resistant GM rice is not allowed in China, the role of CRISPR rice is important because it possesses insect resistance (similar to GM rice) and may be regulated as a non-GM product. Compared to conventional rice, CRISPR rice with no insect pests in lab trials produces an approximately 36 per cent lower yield (Lu et al., 2018). When there are insect pests, the relative yield is ambiguous, however, meaning that partly planting CRISPR rice would be advisable only if CRISPR rice outperformed conventional rice in resistance to insect pest damage.[2] This trade-off indicates an optimal planting share for CRISPR rice, which is precisely the area of the debate to which this paper contributes.

The objective of our ex ante study is to determine the optimal planting share of CRISPR rice from the perspective of a representative farmer (i.e. not considering any environmental externalities of her actions) and to analyse which exogenous factors have the greatest effects on that share. We do so by developing a microeconomic model of a rice farmer who decides the allocation of her land into conventional and CRISPR rice under uncertainty of insect pest severity and considering yield differentials. An essential contribution of our work is to quantify the value of including the CRISPR rice into the farmer's production process compared to conventional rice alone. The theoretical framework we advance enables simulating counterfactuals for evaluating the influence of future actions of the Chinese government regarding CRISPR rice.

Our contribution to the existing and growing literature on CRISPR rice is economically assessing its market potential considering uncertainty about insect pest severity and providing a framework to assess the influence of its factors. For example, Vyska et al. (2016) investigated the trade-off between disease resistance and crop yield in a biological model but did not consider its economic implications. Bartkowski et al. (2018) discussed the economic, ethical and policy implications of CRISPR technology due to the fact that CRISPR crops blur the boundary between nature and technology and result in non-traceability of modifications. However, they did not go into the details about market potential and determinants of the optimal share. Our results have implications for at least three groups of market agents in China. First, farmers (through information campaigns) could use them to decide whether to plant CRISPR rice and, if so, how much. Second, policymakers can use the results as a point of departure to work out the contours of future policies and regulations regarding CRISPR technology and managing uncertainty over market effects due to potentially severe insect pest outbreaks. Third, seed developers and pesticide suppliers will be directly affected by the future share of CRISPR rice in the total land area dedicated to rice production and the determinants of the optimal share.

[2] Partial adoption of CRISPR rice instead of full adoption is most likely because there will always be some farmers who choose not to adopt the new technology.

2. A model

Consider a representative price-taking farmer who grows both CRISPR rice (indexed by $i = \mathrm{C}$) and conventional rice ($i = \mathrm{V}$) on separate fields. The separation assumption reflects the need for different pesticide application rates as well as possible segregation costs implied by the country's regulatory framework. The total area of CRISPR rice is L_C and conventional rice L_V. The farmer uses all available land for rice ($\overline{L}$), which is fixed in a given year, implying $L_C + L_V = \overline{L}$. Although rice can be harvested twice a year depending on climatic conditions and geographical location (Peng et al., 2009), our farmer harvests only once. This assumption does not affect our empirical results, as we use annual aggregate production data for China.

Before planting rice, the farmer faces uncertainty over pest severity. To maintain tractability, we assume two states of nature (indexed by j): a severe state ($j = S$) associated with a pest outbreak and a less severe state ($j = N$), in which the pest occurrence is weak.[3] The probability of the severe state is q, and the probability of the less severe state is $1 - q$.

Farmers typically apply pesticides throughout the growing season and can determine which state of nature has occurred only after a certain amount of time into the season (e.g. the harvest), after which the pest cannot cause any further damage to the yield. Therefore, we assume the farmer makes her decision about pesticide quantity to use before the uncertainty about the pest severity is revealed (similar to land allocation). The farmer will therefore choose the optimal pesticide rate (X_i, in kilograms per hectare). Because our model is static and the unit of time measurement is a year, X is the sum of pesticide amounts applied per hectare per year. CRISPR rice is insect-resistant, so the intensity of pesticide use for CRISPR rice is lower than for conventional rice (Lu et al., 2018); that is, $X_C < X_V$.

In either scenario, the farmer derives her revenues from selling CRISPR and conventional rice, whose production critically depends on the rice yield. Let Y_i denote the yield of rice type i in the absence of pest damage (i.e. in the extreme case when the pest intensity is zero). These yields correspond to points a and b in Figure 1. In a controlled laboratory environment, Y_C is significantly lower than Y_V (e.g. Lu et al. [2018] reported a 36 per cent difference. The market experts we communicated with argued the farmers would accept a maximum difference of 10 per cent; hence, this is the value we used in the numerical part of the model). As pest intensity increases, the yields of both rice types decline. However, because CRISPR rice is insect-resistant, the yield decline will be slower (depicted by the flatter curve in Figure 1) than for conventional rice.

Consider a pest intensity threshold below which the damage is considered less severe and above it is severe. Lacking empirical data, we assume this

[3] In reality, the severity of the pest damage would be a random variable with a continuous distribution. Because pesticide use is not the focus of this paper, however, we model the severity as a binary variable.

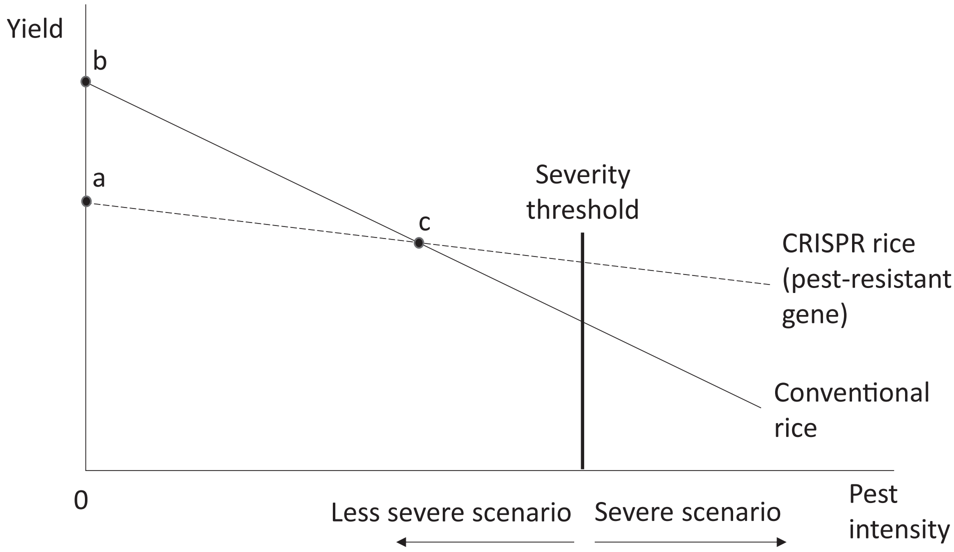

Figure 1 Pest intensity and rice yield under no pest abatement.

threshold is to the right of point c—the intersection of the two yield curves. This is not likely a strong assumption given the insect resistance of CRISPR rice, which brakes the yield decline with respect to pest intensity. The yield of CRISPR rice is higher than the yield of conventional rice in the severe pest scenario, but the outcome does not necessarily reverse in the less severe scenario. Only when pest intensity is between points a and c is the yield of CRISPR rice lower than that of conventional rice.

Denote $\alpha_i \in (0,\ 1)$ as the proportion of the maximum yield left after the severe pest damage given no damage abatement actions. The yield loss is then $(1-\alpha_i)Y_i$. CRISPR rice has a higher percentage of yield left than conventional rice because it is insect-resistant, implying that $0 < \alpha_V < \alpha_C < 1$. The farmer can take precautionary measures and apply pesticides to reduce potential loss. Following Lichtenberg and Zilberman (1986), we denote $G_j(X_i)$ as the abatement function for rice type i in state j. It measures the share of the potential loss that can be averted. More specifically, $G_j(X_i) = 1$ denotes the complete eradication of the destructive capacity, and $G_j(X_i) = 0$ represents zero elimination of the loss. The actual yield of rice type i in state j can thus be written as $\alpha_i Y_i + G_j(X_i)(1-\alpha_i)Y_i$. With this yield, we can write the production of rice type i in state j as

$$Q_{ij} = \left[\alpha_i Y_i + G_j(X_i)(1-\alpha_i)Y_i\right]L_i \tag{1}$$

The price of a pesticide is m dollars per kilogram. The cost related to pesticide use for CRISPR and conventional rice is proportional to the planted area: mX_CL_C and mX_VL_V.

Because the previous literature has documented monopolistic power in the markets for genetically modified seeds (e.g. Dillen et al., 2009), we single out the cost of rice seed. Denoting s_V as the cost of conventional seed per hectare and δ as a percentage by which the monopolist charges more for CRISPR seed compared to the market price of conventional seed, the cost per hectare of CRISPR seed is $s_C = (1+\delta)s_V$. This is the simplest representation of monopolistic pricing of CRISPR seed that is also in line with the price-taking behaviour of the representative farmer that we maintain throughout the paper. It implies that the farmer knows that the monopolist charges more for CRISPR seed than does the (competitive) market for conventional rice but is unaware of the relation between δ and L_C. We vary parameter δ in the Monte Carlo simulations below, thus investigating the effects of the degree of market power on the optimal planting area of CRISPR rice.

Other costs related to the production of CRISPR rice are aggregated in the non-linear term AL_C^{ϵ}, which consists of two parts: first, the cost of fertiliser, machinery and other costs and, second, strictly convex (in land) segregation cost related to the production of CRISPR rice that the farmer faces as a result of the national regulatory framework. The strict convexity of the non-linear part of the CRISPR rice cost is represented by the parameter $\epsilon > 1$, which represents the elasticity of the other cost with respect to the planted area of CRISPR rice (e.g. the larger the area under CRISPR rice, the more efforts the farmer must spend to ensure the two types of rice are segregated to prevent gene flow).[4] The positive parameter A is determined at the calibration stage. The farmer does not incur segregation costs for conventional rice; therefore, all other costs for conventional rice are captured in the constant cost per hectare, φ.[5] The values of parameters A and φ depend on the state of nature (e.g. more labour and energy costs are likely necessary in the severe pest state). The total production cost in state j (c_j) can then be expressed as.

$$c_j = mX_C L_C + s_C L_C + A_j L_C^{\epsilon} + \left(mX_V + s_V + \varphi^j\right) L_V \tag{2}$$

[4] Gene flow is an inevitable natural process (Lu and Snow, 2005) and may cause spatial externalities (Ceddia et al., 2011). CRISPR rice is a self-pollinating plant, but cross-pollination of rice in a field can occur at relatively low rates. In addition, pollen-mediated gene flow of CRISPR rice is expected to disperse to nearby wild, weedy relatives (Lu and Snow, 2005). Therefore, segregation of CRISPR rice is necessary and might be expensive when the planting area is large (Gruère et al., 2011).

[5] It could be argued that other costs are also non-linear with respect to land use. For example, if rice production were expanded to previously unused lands or hillier areas, the cost would likely rise more than proportionally. However, we assume the total area devoted to rice is fixed at $\overline{L}$, making these considerations less of a concern. In the past ten years, the total rice planting area in China has been hovering around 30 million hectares (NBSC, 2018).

Denoting the market price of rice type i as p_i, the farmer's profit in state j is.

$$\pi_j = p_C Q_{Cj} + p_V Q_{Vj} - c_j \tag{3}$$

Following previous empirical studies on the behaviour of Chinese farmers (e.g. Chen et al., 2018; Jin et al., 2017; Liu, 2013), we model the representative farmer as a risk-averter with a strictly concave Bernoulli utility function $u(\pi)$. The farmer maximises the expected utility (EU) by choosing the optimal area of land for CRISPR rice (L_C)[6] and pesticide rates X_C and X_V:

$$\max_{\{L_C,\ X_C,\ X_V\}} EU = qu(\pi_S) + (1-q)u(\pi_N) \tag{4}$$

The optimal values for L_C, X_C and X_V satisfy the first-order conditions.

$$\frac{\partial EU}{\partial L_C} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial L_C} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial L_C} = 0 \tag{5}$$

$$\frac{\partial EU}{\partial X_C} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial X_C} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial X_C} = 0 \tag{6}$$

$$\frac{\partial EU}{\partial X_V} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial X_V} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial X_V} = 0 \tag{7}$$

Finally, the optimal planting share of CRISPR rice (ρ) is equal to $\rho = L_C/\overline{L}$.

3. Specific functional forms

Two general functions from the model outlined above need to be specified to make the model empirically operational: the abatement function $G(X)$ and the Bernoulli utility function $u(\pi)$. Several possible functional forms capture the requisite properties of the abatement function (i.e. it monotonically increases in X, and its values are between zero and one). In the empirical part of the paper, we use the exponential function $G_j(X_i) = 1 - e^{-\lambda_j X_i}$, which requires only one parameter [$\lambda_j \in (0,\ 1)$] to be calibrated in each state of nature (Lichtenberg & Zilberman, 1986).[7] The higher the parameter, the faster the abatement function approaches its maximum. For a given pesticide application rate (X), the effectiveness of the abatement activity is presumably higher in the less severe scenario than the severe one; that is, we require that

[6] The area of conventional rice can readily be determined as $\overline{L} - L_C$.

[7] Apart from requiring only one parameter to calibrate, the exponential specification is also consistent with our baseline data in that it yields the optimal area of CRISPR rice that lies between zero (lower bound) and the total land endowment (upper bound). We also checked the Weibull specification for the damage abatement function, $G = 1 - e^{-X^{\lambda}}$, which also depends only on one parameter. It, however, did not result in an economically feasible solution as the calibrated area of CRISPR rice was more than the total land endowment.

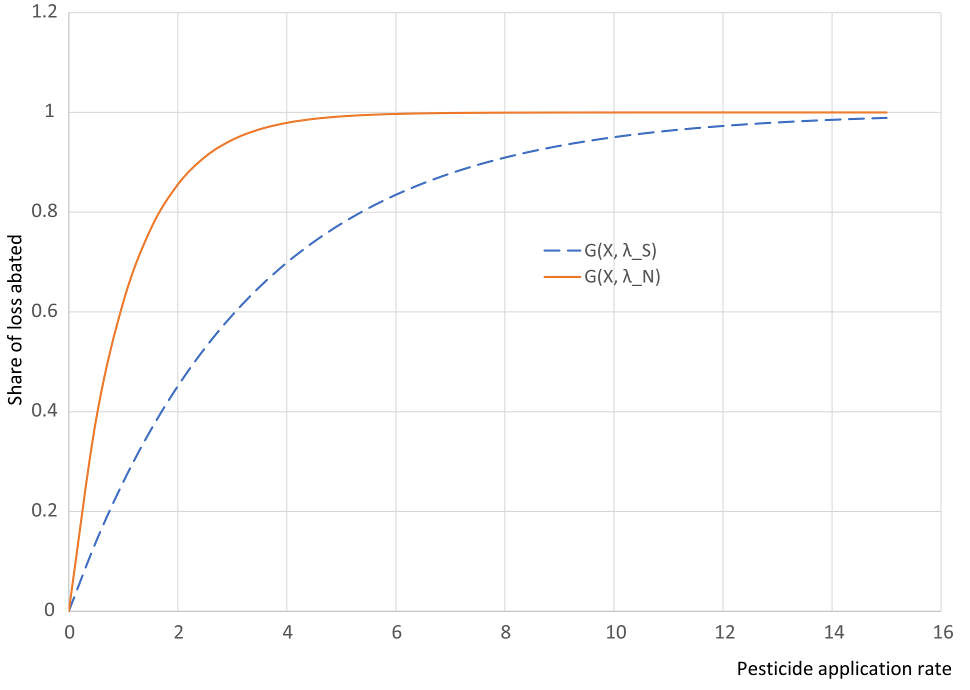

Figure 2 Output damage abatement functions for severe (S) and less severe (N) scenarios. [Colour figure can be viewed at wileyonlinelibrary.com]

$1 - e^{-\lambda_N X} > 1 - e^{-\lambda_S X}$, which implies $\lambda_S < \lambda_N$. Figure 2 illustrates the implication of this condition: the curve corresponding to the share of loss abated in the less severe scenario is above the curve for the severe scenario for any pesticide application rate.

Regarding the Bernoulli utility function, we assume it takes the exponential form $u(\pi) = -e^{-r\pi}$. This is a popular functional form in the empirical literature on uncertainty (e.g. Bodnar, et al., 2018; Lu et al., 2018; Zuhair et al., 1992). It has only one parameter (r), which represents constant absolute risk aversion. This is convenient because, by changing this parameter in the sensitivity analysis later, we can investigate the influence of (constant absolute) risk aversion of the farmer on the model outcomes of interest. Moreover, the parsimony of this function regarding the number of parameters reduces data needs when calibrating our model.

4. Data and model calibration

Data in this study come from the literature on CRISPR and conventional rice, in which Table 1 summarises together with the sources. Where the data on CRISPR rice are not available (e.g. pesticide application rate and cost), we use the data from Bt rice field trials (Huang et al., 2005) as a proxy, since both rice types are insect-resistant.

Table 1 Data and sources

Parameter	Symbol	Baseline value	Source	Minimum	Maximum	Source of max./min.
Price of CRISPR rice (1000 $/ton)	p_C	0.164	Index Mundi (2020)	0.164	0.356	Historical data from 1997–2006, Index Mundi (2020)
Price of conventional rice (1000 $/ton)	p_V	0.182	Assumed based on Pray et al. (2001)	0.164	0.356	Historical data from 1997–2006, Index Mundi (2020)
Percentage of max. CRISPR rice yield after the most severe insect pest damage	α_C	0.810	Average of the interval provided by He et al. (2016)	0.650	0.970	He et al. (2016)
Percentage of max. conv. rice yield after the most severe insect pest damage	α_V	0.640	Average of the interval provided by Xu et al. (2017)	0.400	0.880	Xu et al. (2017)
Price of pesticide (100 $/kg)	m	0.001	Personal communication	0.001	0.002	30% variation
Max. yield of CRISPR rice (ton/hectare)	Y_C	6.975	$0.9 \times Y_V$ based on communication with experts	4.883	9.068	30% variation
Max. yield of conv. rice (ton/hectare)	Y_V	7.750	NBSC (2020)	7.625	7.875	Historical data from 1997–2006, NBSC (2020)
Total rice area (million hectares)	$\overline{L}$	28.50	NBSC (2020)	26.50	31.80	Historical data from 1997–2006, NBSC (2020)
Shape parameter of the abatement function under weak pests	λ_N	0.969	Calibrated	0.678	1.260	30% variation
Shape parameter of the abatement function under severe pests	λ_S	0.005	Calibrated	0.004	0.007	30% variation
Parameter of other costs of CRISPR rice	A	0.145	Calibrated	0.102	0.189	30% variation
Probability of severe insect pests	q	0.341	Jiaan Cheng (2009)	0	1	Definition
Segregation cost parameter	ϵ	1.500	Calibrated	1.422	1.522	30% variation
	r	0.090	Chen et al. (2018)	0.070	0.110	Chen et al. (2018)

Table 1 (*Continued*)

Parameter	Symbol	Baseline value	Source	Minimum	Maximum	Source of max./min.
Constant absolute risk aversion						
Other costs per hectare of conventional rice under weak pest (1000 \$/hectare)	φ_S	0.862	R. Hu, priv. communication (2018)	0.603	1.120	30% variation
Other costs per hectare of conventional rice under severe pest (1000 \$/hectare)	φ_N	0.862	R. Hu, priv. communication (2018)	0.603	1.120	30% variation
Cost per hectare of CRISPR rice (1000 \$/hectare)	UC_C	0.521	Assumed the same as for Bt rice; R. Hu, priv. communication (2018)	The confidence interval is not provided here because UC_C is not directly used in Monte Carlo simulations.		
Elasticity of land used for CRISPR rice with respect to the marginal cost of CRISPR rice production	η	2.121	Assumed	The confidence interval is not provided here because η is not directly used in Monte Carlo simulations.		
Monopoly surcharge in the CRISPR rice seed market compared to conventional seed (relative number)	δ	0.652	Calibrated	0.000	2.000	Assumed
Price of conventional rice seed (1000 \$/hectare)	s_V	0.023	R. Hu, priv. communication (2018)	0.013	0.036	R. Hu, priv. comm.(2018)
Price of CRISPR rice seed proxied by GM rice seed (1000 \$/hectare)	s_C	0.037	R. Hu, priv. communication (2018)	$s_C = (1 + \delta)s_V$		

We set the price of CRISPR rice equal to the price of conventional rice in the baseline. However, previous literature on the price relationships between similar GM and conventional crops (e.g. Brookes et al., 2010; Pray et al., 2001) has argued that farmers growing GM crops can afford to accept lower market prices because the total costs of cultivating GM crops are less than the costs of non-GM crops due to fewer inputs (e.g. pesticides or labour) and the benefits of reduced inputs outweigh the higher seed costs. Therefore, in later Monte Carlo simulations, we relax the baseline assumption and keep the price of CRISPR rice below that of conventional rice (i.e. $p_C \leq p_V$). Similarly, our baseline assumption is that other costs per hectare of conventional rice are equal under both weak and severe pest damage (i.e. $\varphi_N = \varphi_S$). We relax this assumption in the sensitivity analysis as well and investigate what effect different relative costs per hectare of conventional rice have on the optimal planting share.

The parameter r of the exponential Bernoulli utility function equals constant absolute risk aversion, and in the baseline, we set it to $r = 0.09$, as reported by Chen et al. (2018). The higher this value, the more risk-averse the farmer is, ceteris paribus.

To reduce the number of calibrated parameters (due to a lack of necessary data), we set the calibrating constants A_S and A_N of the function for other cost of CRISPR rice equal—that is, they do not depend on the state of nature —to make the (segregation) cost of CRISPR rice less sensitive to pest severity. With this assumption, there are four unknown parameters (λ_S, λ_N, A and ϵ) and one variable (L_C) to be calibrated using the baseline data.

The first-order conditions [5]–[7] (more precisely, their specific equivalents presented by [A1]–[A3] in Appendix 1), in principle, determine λ_S, λ_N and L_C. To calculate the parameters A and ϵ, we need two more equations. Based on equation [2], the cost of cultivating CRISPR rice is

$$C_C = mX_C L_C + s_C L_C + AL_C^{\epsilon}, \tag{8}$$

from which the corresponding marginal cost is $MC_C = mX_C + s_C + \epsilon AL_C^{\epsilon-1}$. Let η be the elasticity of land use with respect to the marginal cost of CRISPR rice:

$$\eta = \frac{\partial L_C}{\partial MC_C} \frac{MC_C}{L_C} = \frac{mX_C + s_C + \epsilon AL_C^{\epsilon-1}}{\epsilon(\epsilon - 1)AL_C^{\epsilon-1}}. \tag{9}$$

We can use equation [8] to calculate the production cost per hectare of CRISPR rice (UC_C) as $UC_C = C_C/L_C = mX_C + s_C + AL_C^{\epsilon-1}$, from which $AL_C^{\epsilon-1} = UC_C - mX_C - s_C$. Substituting the right-hand side of the previous equation into [9] and rearranging, we obtain.

$$\epsilon^2 - \frac{1+\eta}{\eta}\epsilon - \frac{mX_C + s_C}{\eta(UC_C - mX_C - s_C)} = 0, \tag{10}$$

which is a quadratic equation in ϵ. Finally, the calibrating constant A can be obtained by rearranging the unit cost function as.

$$A = (UC_C - mX_C - s_C)/L_C^{\epsilon-1}. \tag{11}$$

In summary, we obtain the four unknown parameters and one variable by simultaneously solving equations [A1], [A2], [A3] (Appendix 1), [10] and [11].

The per-hectare production cost of CRISPR rice is not known at the moment, as the rice is not yet grown commercially. To overcome this information gap, we use the cost of Bt rice instead and set UC_C = 521.3 US dollars per hectare (R. Hu, private communication, 2018). Regarding the elasticity of land use with respect to the marginal cost of CRISPR rice, we assume $\eta = 2.12$, as CRISPR rice is not grown yet. We let the model guide us in choosing the specific value of this parameter.

We pose some structure on the underlying data. We use specific functions to operationalise the theoretical model; we constrain the space for some parameters and require specific relationships between them (e.g. $0 < \lambda_S,\ \lambda_N < 1$ and $\lambda_S < \lambda_N$); we require strict convexity for the other CRISPR cost function (i.e. $\epsilon > 1$) so the optimisation problem has a unique optimal solution; and we require the optimal land use for CRISPR rice to be positive and not exceed the total allocation of land for rice. The toll we pay to simultaneously satisfy all these restrictions is a narrow manoeuvring space for the elasticity η in the baseline. By calibration, we find the lower bound to be 1.99 and the upper bound 2.23; therefore, our choice of η is between them. It should be noted that η is an auxiliary parameter that we use only in the baseline. In the Monte Carlo simulations later, we vary parameter ϵ, which is directly linked to η, as per [10].

Finally, we determined the baseline value of parameter δ through an iterative process. Since we know the price of conventional rice seed (s_V), we kept changing the value of δ until the calculated value of CRISPR rice seed (s_C) (for which there are no historical observations yet) was equal to the price of GM rice seed, which we use as a proxy for the price of CRISPR rice seed. Although it might be tempting to use the earlier formula, $s_C = (1+\delta)s_V$, to calculate the value of δ from the price of conventional rice seed, it turns out that this approach does not generate the target CRISPR rice seed price in equilibrium. This is because the model-wide effects need to be considered as well.

Numerically solving equations [A1], [A2], [A3], [10] and [11], we obtain $\lambda_S = 0.005$, $\lambda_N = 0.969$, $A = 0.145$, $\epsilon = 1.500$ and $L_C = 10.8$ million hectares.

5. Baseline model results

The optimal planting share of CRISPR rice in the baseline is 37.9 per cent (=10.8/28.5), and the expected profit from planting both types of rice is 12.45 billion US dollars at a 0.341 baseline probability of severe pest outbreak. This result, however, does not solve the farmer's dilemma mentioned in the title of this paper: for a given probability of pest outbreak, would the farmer be better off planting both types of rice or just sticking to conventional rice? Using our baseline model, we calculate that the farmer's expected profit in a counterfactual scenario with conventional rice only and the same probability of severe pest outbreak as the baseline is 9.85 billion US dollars. Thus, the difference in the expected values of profit between cultivating both types of rice and conventional rice alone is 2.6 billion US dollars. (We do not calculate the benefits of cultivating CRISPR rice only, as presumably some farmers will always choose not to adopt the new technology.)

Table 2 sheds more light on the discussion above by presenting results decomposed by pest severity and rice type with the baseline data and an assumption that yields of CRISPR rice are 10 per cent lower than conventional rice. The first row presents profits in billion US dollars, and the second row quantifies profit per hectare.

Clearly, profits in the severe case are significantly lower than in the weak pest case. Looking at the relative difference, the gap for CRISPR rice is −33.8 per cent (4.44/6.71–1) but is much more pronounced for conventional rice (−87.6 per cent, i.e. 1.15/9.29–1). This suggests that the profitability of conventional rice is much more sensitive to uncertainty of pest outbreak than CRISPR rice (which is insect-resistant). This calculation also agrees with the observed reversal of the profitability of conventional rice relative to CRISPR rice (i.e. 9.29 billion US dollars vs. 6.71 billion in the weak pest case compared to 1.15 billion vs. 4.44 billion in the severe case) in the first row of Table 2.

Based on profits per hectare, we expect the farmer to favour CRISPR rice, as it can generate almost 18.5 per cent more profit per hectare in the weak pest scenario (622/525–1) and more than six times more in the severe pest scenario (411/65). The values in Table 2 also indicate that growing both rice

Table 2 Profits from rice production under various scenarios

	Severe pest			Weak pest		
	Both types planted			Both types planted		
	CRISPR	Conv.	Only conv.	CRISPR	Conv.	Only conv.
Total profit from a rice type i (billion \$)	4.44	1.15	1.79	6.71	9.29	14.03
Profit per hectare (\$/ha)	411	65	63	622	525	492

types simultaneously benefits the farmer, as the difference between profits in the severe and weak pest cases for conventional rice alone is −87.2 per cent (1.79/14.03–1) but decreases to −65.1 per cent [(4.44 + 1.15)/(6.71 + 9.29)–1] when both types are grown.

The representative farmer in our model is risk-averse. The certainty equivalent corresponding to the baseline values and the assumed exponential Bernoulli utility function is 11.28 billion US dollars. The resulting risk premium is thus 1.17 billion US dollars (12.45 billion–11.28 billion), which means that 1.17 billion US dollars is the minimum amount by which the expected profit must exceed the certainty equivalent to induce the farmer to bear the uncertainty of pest severity.

We conclude this section by providing break-even values for four selected parameters that might be useful both to policymakers and technology developers. The break-even values correspond to a situation where the optimal decision of the representative farmer would be not to grow any CRISPR rice, that is $L_C = 0$.

We start with the yield drag. Based on the values in Table 1, we calculated the baseline value of this parameter to be −10 per cent (=6.975/7.750–1). Holding all other parameters at their baseline levels, the yield of CRISPR rice would have to decrease to 5.011 tons per hectare for the farmer not to grow CRISPR rice. This implies the break-even yield drag of −35.3 per cent (=5.011/7.750–1). A reader might recall that Lu et al. (2018) reported a yield drag of −36 per cent for CRISPR vs conventional rice in a controlled laboratory environment. It might appear that if Lu et al. (2018) are right, then there would be no planting of CRISPR rice. This conclusion is not correct, however. The reason is that the yield drag in our baseline is −10 per cent (not −36 per cent) (see the section on model description), which means that had we used −36 per cent as reported in Lu et al. (2018), the break-even value of the yield drag would have been lower than −35.3 per cent.

In the baseline, CRISPR rice is sold at a discount of 10 per cent (=0.164/0.182–1). Our break-even analysis shows that, other things kept equal, the price of CRISPR rice would have to decrease to 0.118 US dollars per ton for $L_C = 0$. This implies a break-even price discount of almost 65 per cent (=0.118/0.182–l).

The third break-even value we calculate is the technology fee for CRISPR rice. The break-even price of CRISPR rice seed turns out to be 3,388 US dollars per hectare. This extraordinarily high value is more than 90 times greater than the baseline cost of CRISPR seed and more than 150 times greater than the baseline cost per hectare of conventional seed. These relative differences suggest that the optimal area under CRISPR rice will not change much compared to the baseline when the degree of market power—proxied by the relative difference between the cost of CRISPR and conventional rice—reaches a realistically conceivable level (e.g. we assume 200 per cent in the sensitivity analysis below).

The final parameter whose break-even value we analyse is the segregation cost per hectare. Following our specification of the total segregation cost in equation 2, the segregation cost per hectare (s) equals $s = AL_C^{\epsilon}/L_C = AL_C^{\epsilon-1}$. Because $ds/dL_C = (\epsilon - 1)AL_C^{\epsilon-2} > 0$ for $\epsilon > 1$ (which we require for the total segregation cost to be convex in the area of CRISPR rice), it must be that the smaller is the area of CRISPR rice, the lower is the per hectare segregation cost; in particular, as L_C approaches zero, so does the segregation cost per hectare.

Clearly, the baseline results depend on the chosen parameters. To check how robust they are, in the following section, we run sensitivity analysis using Monte Carlo simulations.

6. Sensitivity analysis of the baseline results

We start by generating a PERT[8] distribution for each parameter of interest (Table 1) from which we then randomly draw the parameter values 100,000 times, each time running the model and recording the results. We use the PERT distribution because of its minimum prior information requirements: the maximum, minimum and most probable value (mode) of a parameter. Better than other distributions, the PERT distribution constructs a smooth curve with the expectation that the resulting value will be around the most likely value (Davis, 2008).

Table 1 presents the baseline values of the parameters that we use as the mode of the PERT distribution. If a parameter has natural limits (e.g. probability of pest severity), we use those for the minimum and maximum. In the remaining cases, we rely on the previous literature (e.g. percentage of conventional yield left after severe pest damage), historical data (e.g. market price of conventional rice per hectare) or in the absence of sources, we either set the lower (upper) bound to be 30 per cent below (above) the baseline value or assume a specific interval (for parameter δ). Table 1 provides the sources of individual confidence intervals. We perform the Monte Carlo simulations with 'nleqslv' package in *R × 64 4.0.5* (Fletcher, 2012; Hasselman, 2018; R Core Team, 2021).

Before turning to the sensitivity analysis results, note that not all results of the 100,000 model runs were considered. First, we excluded the infeasible solutions, that is, those where the planting share was either negative or greater than one. These solutions can occur in numerical simulations for some assemblages of model parameters. Second, for other constellations of exogenous parameters, the model could not find the optimal solution (problems with convergence) most likely due to the model's non-linearities and starting values that might not be close enough to the solution. In the end, we included the results of 92,852 model runs (i.e. almost 93 per cent) in the sensitivity analysis.

[8] Project Evaluation and Review Technique

Figure 3 depicts the kernel density function of the optimal planting share based on the successful 93 per cent of model runs. The median of the planting share is 22.7 per cent, and the mean is 26.0 per cent. These values need to be juxtaposed with the percentage calculated in the baseline (37.9 per cent). Clearly, the uncertainty over model parameters also translates into the value of the planting share. For completeness, the standard deviation of the distribution in Figure 3 is 18.0 percentage points.

Table 3 shows more detailed sensitivity results for the optimal planting share, expected profit, certainty equivalent and risk premium. We distinguish between the case where both rice types are planted and where the farmer grows only conventional rice. Both scenarios are run in one iteration, and the process is repeated 100,000 times. In each iteration, we randomly draw from the distributions of individual parameters. With those parameters, we calculate the variables of interest for both types of rice and for conventional rice only. Due to the model structure change in the second scenario (from three equations to one), the number of feasible and optimal model runs decreases from 92,852 (as reported in Figure 3) to 53,281.

Table 3 shows that the expected profit and certainty equivalent of the risk-averse farmer growing rice are greater when both types of rice are grown than when conventional rice only is grown. Notice that the farmer requires a smaller risk premium when her rice production is more diversified. This confirms the baseline result that the farmer benefits from diversifying her production by including CRISPR rice. More broadly, our findings can also be linked to the discussion of agrobiodiversity as natural insurance to risk-averse farmers and to society by reducing the uncertainty in the provision of public-good ecosystem services (Baumgärtner & Quaas, 2010; Quaas & Baumgärtner, 2008).

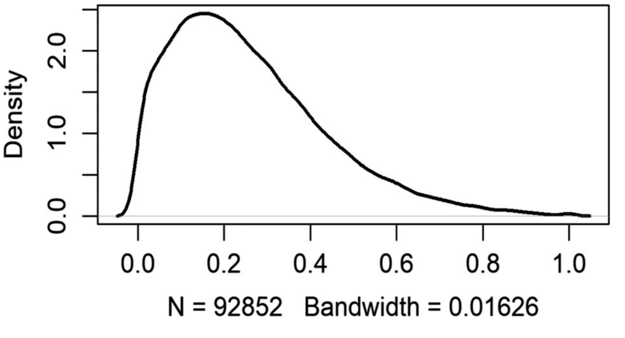

Figure 3 Kernel density function of the optimal planting share of CRISPR rice. *Note*: The horizontal axis represents the optimal planting share of CRISPR rice. The median and the mean are 22.7 per cent and 26.0 per cent respectively; the standard deviation is 18.0 percentage points. The actual values on the horizontal axis are between zero and one. However, the R software does not truncate the kernel density function at zero and one, slightly extending it beyond the given limits instead.

Table 3 Results of the Monte Carlo simulations (N = 53,281) (billion US dollars)

	Min.	1st quartile	Median	Mean	3rd quartile	Max.	Standard deviation
CRISPR rice and conventional rice							
Optimal share (%)	0.00	12.60	22.93	26.18	36.21	100.00	17.97
Expected profit	−0.04	13.04	16.49	16.96	20.61	42.80	5.43
Certainty equivalent	−1.00	11.95	15.25	15.69	19.10	41.00	5.21
Risk premium	0.00	0.73	1.17	1.27	1.70	5.26	0.71
Conventional rice only							
Expected profit	−4.91	10.34	14.20	14.64	18.76	37.43	5.97
Certainty equivalent	−6.24	8.93	12.64	13.02	16.87	35.86	5.76
Risk premium	0.00	0.90	1.51	1.62	2.21	6.58	0.94
Value of co-planting CRISPR rice	−3.33	1.01	1.85	2.32	3.15	12.66	1.75

So, what is the value of co-planting CRISPR rice in addition to conventional rice? We define this value as the difference between a farmer's expected profit with both types of rice and with conventional rice only. The last row in Table 3 gives the estimates.[9] The median of the value of co-planting CRISPR rice is 1.85 billion US dollars, and the mean is 2.32 billion US dollars, suggesting a distribution of the values skewed to the right. Overall, in 99 per cent of the cases, we find a positive value of co-planting CRISPR rice. Figure 4 depicts the results.

7. What affects the optimal planting share of CRISPR rice the most?

The amount of land devoted to CRISPR rice and its determinants is likely to be of interest to several market agents, especially the seed industry and governments. Various parameters have different units, and therefore, we cannot directly compare the influence of various parameters on the optimal share. However, converting the dependent variable (optimal share) and independent variables (exogenous parameters) into logs, an ordinary least square regression on the converted variables yields coefficients that, by construction, represent elasticities of the optimal share with respect to individual parameters. The higher the absolute value of an elasticity, the stronger the effect of a parameter on the optimal planting share. Table 4 presents the results.

The signs of all regression parameters are significant at the 1 per cent level and consistent with theoretical expectations. The five most influential parameters are ϵ, p_V, Y_V, p_C and Y_C. At the risk of over-extending the results, three main factor groups appear to affect the optimal planting share of CRISPR rice in China: the regulatory environment (especially the

[9] The values in the last row of Table 3 are not equal to a difference between the expected profit values in the lines above because the presented values in either scenario do not necessarily correspond to the same model run.

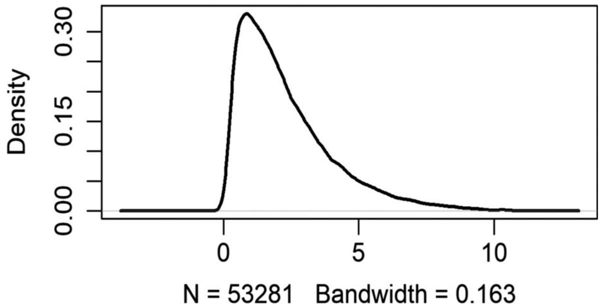

Figure 4 Kernel density function of the value of adopting CRISPR rice. *Note*: The horizontal axis represents values in billion US dollars. The median, mean and standard deviation are 1.85, 2.32 and 1.75 billion US dollars respectively.

Table 4 Relative impacts of exogenous parameters on the optimal planting share (all parameters in the OLS regression were converted into logs) (N = 92,852)

Parameter	Symbol	Estimate	P value
Price of CRISPR rice (1000 $/ton)	p_C	5.28***	0.0000
Price of conventional rice (1000 $/ton)	p_V	−6.37***	0.0000
Percentage of max. CRISPR rice yield after the most severe insect pest damage	α_C	2.07***	0.0000
Percentage of max. conv. rice yield after the most severe insect pest damage	α_V	−1.62***	0.0000
Price of pesticide (100 $/kg)	m	0.42***	0.0000
Max. yield of CRISPR rice (ton/hectare)	Y_C	4.27***	0.0000
Max. yield of conv. rice (ton/hectare)	Y_V	−5.54***	0.0000
Total rice area (million hectares)	$\overline{L}$	−0.78***	0.0000
Shape parameter of the abatement function under weak pests	λ_N	0.04**	0.0014
Shape parameter of the abatement function under severe pests	λ_S	−0.42***	0.0000
Parameter of other costs of CRISPR rice	A	−2.01***	0.0000
Probability of severe insect pests	$\boldsymbol{q}$	0.20***	0.0000
Segregation cost parameter	ϵ	−7.21***	0.0000
Constant absolute risk aversion	r	0.13***	0.0000
Other costs per hectare of conventional rice under weak pest (1000 $/hectare)	φ_N	1.05***	0.0000
Other costs per hectare of conventional rice under severe pest (1000 $/hectare)	φ_S	2.05***	0.0000
Conventional seed cost (1000 $/hectare)	a	−0.04***	0.0000
Monopoly power	δ	−0.01***	0.0000
Intercept		3.63***	0.0000
	Adjusted R^2	0.82	

Note: ***Statistical significance at <0.001. **Statistical significance at <0.01.

segregation costs associated with ϵ), the market situation (represented by the market prices of CRISPR and conventional rice, p_C and p_V), and the state of the technology (proxied by the potential yields of CRISPR and conventional rice, Y_C and Y_V). Of these three groups, seed quality (translated into potential yield) is the one over which seed producers have direct control.

Regarding the relationship between a farmer's (constant absolute) risk aversion (r) and the optimal planting share of CRISPR rice, the positive and highly significant coefficient means that a more risk-averse farmer tends to prefer a higher share of CRISPR rice (as it brings higher expected profit than conventional rice alone). The negative sign of the coefficient on the total rice acreage indicates that growing urbanisation in China could increase the acreage share of CRISPR rice to the detriment of conventional rice (provided that commercialisation of CRISPR rice is allowed in the future).

8. Conclusions

CRISPR technology has been booming in the past thirty years, and it has enhanced plant breeding by making it faster, less costly and more precise (Cao, 2018). With respect to CRISPR rice, scientists expect to try alternatives or complementary approaches to insect resistance by combining other engineering methods to minimise adverse effects on yield (Lu et al., 2018), which currently hampers potential commercialisation. CRISPR rice is insect-resistant like GM rice while simultaneously indistinguishable from rice developed by traditional breeding techniques. It is currently under debate how the Chinese government will regulate CRIPSR technology. Therefore, there is a chance that CRISPR rice will not be officially considered a GM product in China. The advantage is evident, since a slow approval process has hindered the commercialisation of new GM crops (Jin et al., 2019), and the largest potential constraint to commercialisation is regulatory delay (Kalaitzandonakes et al., 2007). Meanwhile, people are concerned about food ethics, governance and further concentrate power in the hands of corporate actors (Bartkowski et al., 2018; Clapp & Ruder, 2020).

The future of CRISPR rice is uncertain given the controversy over genome editing regulations in China. One thing is clear: to improve the optimal planting share of CRISPR rice under uncertainty about insect pest severity, which we estimate to be around 38 per cent under our baseline assumptions, scientists must improve the technical performance of CRISPR rice to enable market entry regardless of government regulation on the strictness of segregation.

Planting CRISPR rice along with conventional rice bears a high likelihood of economic benefits compared to conventional rice alone. Based on our model, our mean estimate of this benefit is estimated to be 2.32 billion US dollars annually under uncertainty about the pest severity. This result should, however, be interpreted cautiously as our model is based on several simplifying assumptions, including optimising farmers, spatially homogenous pest risk, no effects of spatial configuration on pest outbreaks (e.g. no spatial spillovers), or that farmers do not adjust pesticide use according to pest infestation.[10]

[10] We are grateful to an anonymous reviewer for pointing out these limitations to us.

Although our results show significant potential for CRISPR rice to enter the Chinese market, we are aware that this optimism might be underpinned by the assumptions we had to make. First, not all data are available, especially those related to the production of CRISPR rice. In that case, we adopted information for Bt rice, which, although similar, is not the same as CRISPR rice. Second, we modelled the optimal planting share of CRISPR rice solely from the perspective of a farmer who does not consider environmental externalities related to pesticide and fertiliser use, to mention but a few. These considerations might be important in the future, should the Chinese government regulate these negative environmental externalities more strictly. We expect that including these effects would increase the share of CRISPR rice. Third, we considered a representative farmer from China. However, the climatic and production conditions in China vary, as do the production costs of rice in different regions. Further research zooming into regional differences is certainly needed. That said, once the new data for CRISPR (and conventional) rice become available, the framework outlined in this article can be readily (updated and) used to generate more precise results. Last but not least, future research will need to look into which functional forms best describe the decision making of farmers and how precisely the pest damage is abated, depending on the amount of the pesticide use.

The decision of China about the approval and commercialisation of CRISPR rice will be crucial for the United States and the European Union, as China is a large global producer of rice. Inconsistent regulatory rules in different countries about CRISPR technology might affect international trade by coexisting with conventional products. Regulations will also influence the direction of research and development of plant-breeding companies, their focus on potential target markets and the future development of CRISPR technology in general.

Conflict of interest

The authors have no conflict of interest to declare.

Data availability statement

The data that support the findings of this study are available upon request.

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Appendix 1

First-order conditions corresponding to the specific functional forms of the model

Using the functional forms specified earlier, first-order conditions [5]–[7] can be written as

$$\begin{aligned}\frac{\partial EU}{\partial L_C} = qre^{-r\pi_S}&\left\{\begin{array}{c} p_C\left[\alpha_C Y_C + \left(1-e^{-\lambda_S X_C}\right)(1-\alpha_C)Y_C\right] \\ -p_V\left[\alpha_V Y_V + \left(1-e^{-\lambda_S X_V}\right)(1-\alpha_V)Y_V\right] \\ -\left[mX_C + s_C + \epsilon A L_C^{\epsilon-1} - \left(mX_V + s_V + \varphi^S\right)\right]\end{array}\right\} \\ +(1-q)re^{-r\pi_N}&\left\{\begin{array}{c} p_C\left[\alpha_C Y_C + \left(1-e^{-\lambda_N X_C}\right)(1-\alpha_C)Y_C\right] \\ -p_V\left[\alpha_V Y_V + \left(1-e^{-\lambda_N X_V}\right)(1-\alpha_V)Y_V\right] \\ -\left[mX_C + s_C + \epsilon A L_C^{\epsilon-1} - (mX_V + s_V + \varphi^N)\right]\end{array}\right\} = 0\end{aligned} \tag{A1}$$

where

$$\pi_S = p_C Q_{CS} + p_V Q_{VS} - mX_C L_C - s_C L_C - AL_C^{\epsilon} - \left(mX_V + s_V + \varphi^S\right)\left(\overline{L} - L_C\right)$$
$$\pi_N = p_C Q_{CN} + p_V Q_{VN} - mX_C L_C - s_C L_C - AL_C^{\epsilon} - (mX_V + s_V + \varphi^N)\left(\overline{L} - L_C\right)$$

$$\begin{aligned}\frac{\partial EU}{\partial X_C} = qre^{-r\pi_S}&\left\{p_C(1-\alpha_C)Y_C L_C \lambda_S e^{-\lambda_S X_C} - mL_C\right\} + \\ (1-q)re^{-r\pi_N}&\left\{p_C(1-\alpha_C)Y_C L_C \lambda_N e^{-\lambda_N X_C} - mL_C\right\} = 0\end{aligned} \tag{A2}$$

$$\begin{aligned}\frac{\partial EU}{\partial X_V} = qre^{-r\pi_S}&\left\{p_V(1-\alpha_V)Y_V\left(\overline{L} - L_C\right)\lambda_S e^{-\lambda_S X_V} - m\left(\overline{L} - L_C\right)\right\} + \\ (1-q)re^{-r\pi_N}&\left\{p_V(1-\alpha_V)Y_V\left(\overline{L} - L_C\right)\lambda_N e^{-\lambda_N X_V} - m\left(\overline{L} - L_C\right)\right\} = 0\end{aligned} \tag{A3}$$

Notice that the term L_C can be cancelled out in [A2], as $L_V = \overline{L} - L_C$ can be in [A3], such that the first-order conditions for X_C and X_V do not directly depend on land areas, which makes intuitive sense because X represents the application of pesticide per hectare. However, there is also an indirect effect via the profits π_S and π_N (in the exponents of [A2] and [A3]) that depend on the allocation of the total land area to L_C and L_V.