Landscape-level feedbacks in the demand for transgenic pesticidal corn in the Philippines

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Abstract

We introduce a novel econometric approach to estimate economic pest control feedbacks within agroecological systems, using discrete choice endogenous sorting models. We apply this approach to deployment of transgenic Bt maize in the Philippines. We show with basic theory how areawide pest suppression from largescale Bt maize deployment attenuates farmers' demand for this technology. Econometric results support this hypothesis and imply long-run demand for the Bt trait is price-inelastic, contrasting with price-elastic demand estimated from a model without feedback. Investigating whether this feedback truly derives from areawide pest suppression, we analyze farmers' pest infestation expectations and find expected damages are significantly reduced by higher areawide Bt deployment. We discuss implications of these findings and other potential applications of the econometric approach to study coupled biological and economic systems.

JEL codes: C33, C35, C36, D24, Q12, Q57
Keywords: agroecology, bioeconomic feedbacks, areawide pest suppression, crop choice, discrete choice models, endogenous sorting

1 Introduction

Largescale agricultural production involves ecological feedbacks between farmer decisions, their effects on biological systems, and economic reactions to these effects. The control of crop pests provides a particularly salient example. Credible estimates put global crop losses due to pests at roughly a quarter of potential yields (Oerke 2006; Culliney 2014), with pest damages expected to increase with climate change (Deutsch et al. 2018). Pest control choices strongly influence economic returns from crop production (Fernandez-Cornejo et al. 2014; Chambers, Karagiannis and Tzouvelekas 2010). A growing body of entomological and weed science research shows how these choices can impose externalities on neighboring farms, by altering landscape-level pest pressure (Hutchison et al. 2010; Wan et al. 2012; Dively et al. 2018),[1] background presence and movement of chemical pesticides (Werle et al. 2018), and the genetic composition (e.g. pesticide resistance) of pest populations (Gould, Brown and Kuzma 2018).

Theoretical and simulation-based models in biology and economics suggest that externalities resulting from such agroecological feedbacks would impact farmers' incentives and decisions to undertake pest control efforts (Milne et al. 2015; Epanchin-Niell and Wilen 2015). However, no empirical research has yet investigated whether this is the case. This is at least partly due to the difficulty of such an exercise. The econometric measurement of such feedback loops would require largescale, landscape-level experiments or – barring these – some strategy to address endogeneity. Moreover, directly observing the interactions between farmers and pest populations requires biological and economic data with enough detail and variation at both the farm and landscape scales.

In this paper we introduce a novel approach to econometrically measure the effect of bioeconomic pest control feedbacks on agents' choices, by using endogenous sorting models developed in the environmental, resource and urban economics literatures (Bayer and Timmins

2007; Timmins and Murdock 2007; Hicks, Horrace and Schnier 2012; Bernasco et al. 2017).[2] These tools have been specifically developed to measure how the choices of individual economic agents depend on the market-level, aggregate demand shares for discrete alternatives, and in turn how these endogenous choices feed back into determining aggregate demand. For example, demand for recreation areas is likely to attenuate with increased congestion (Timmins and Murdock 2007). The key analogue we use here is the hypothesis, based on previous agroecological research, that demand for a specific pest control technology – genetically modified *Bacillus thuringiensis* (Bt) maize – should attenuate due to landscape-level pest pressure reductions induced by the technology.

The general identification strategy used in endogenous sorting models is to observe variation in the effective choice set available within each market. Such variation can be used to build an instrument that predicts variation in aggregate demand shares, but is exogenous with respect to unobserved market-level factors that affect individual preferences and thereby aggregate demand. For example, recreation site openings or closures – or more generally changes in the relative costs of access or nonmonetary attributes – over time produces variation in the effective recreation choice set available at a given interval of time (Timmins and Murdock 2007). To the extent this variation is exogenously determined (i.e. not itself a product of congestion), it can be used to infer how congestion attenuates demand.

To apply this approach in measuring the bioeconomic pest control feedbacks, we first present a simple conceptual model showing how an analogous feedback should manifest in the case of Bt maize, given reasonable – and testable – assumptions about agents' pest damage expectations. In this model greater areawide adoption of Bt maize reduces landscape-level pest pressure, thereby reducing the incentive for individual farmers in the area to deploy the control measure. One practical consequence of recognizing this bioeconomic feedback is that the long-run, equilibrating price elasticity of demand for the pest control measure should therefore be less than what would be erroneously implied by ignoring it. Our empirical estimates in fact suggest demand for the Bt trait switches from being price-elastic to inelastic when accounting for this endogeneity.

Motivated by this theory, we then specify and estimate an endogenous sorting model of pest control decisions, using data on the deployment of genetically modified, Bt maize in the Philippines. Bt crops express insecticidal toxins (which, in nature, are produced by Bt bacteria) that are highly effective at killing and preventing damage from economically important pests. A largescale analysis of Bt maize deployment in the Midwestern U.S., by Hutchison et al. (2010), showed that European corn borer (*Ostrinia nubilalis*, or ECB) – once one of the most historically significant pests of maize in the region – was effectively eliminated by the widespread deployment of Bt varieties. In particular, Hutchison et al. (2010) showed that widespread use of these varieties decreased abundance of the pest on both Bt and non-Bt maize over the landscapes studied. Based on this observation, they estimated the majority of the net benefits from eliminating this pest were accrued by non-users of Bt varieties, who avoided paying the additional costs for the proprietary seeds. Subsequent entomological research in a variety of agricultural systems has added to the evidence for areawide pest suppression by Bt crops (Wan et al. 2012; Dively et al. 2018). In the context of our study, a key related pest in Philippine maize farming systems is the Asian corn borer (*Ostrinia furnicalis*, or ACB). Bt varieties are also highly effective at suppressing ACB (Afidchao et al. 2013).

We first estimate an endogenous sorting model for Philippine maize farmers' decisions to deploy Bt versus non-Bt varieties, using a two-stage fixed effects conditional logit and instrumental variables regression method originally developed by Bayer and Timmins (2007). The results from our estimation confirm the prediction of our conceptual model: Greater areawide adoption of Bt varieties appears to attenuate individual demand for them. As noted above, in qualitive terms, the endogeneity appears to generate price-inelastic long-run demand for the Bt trait. To corroborate the bioeconomic explanation for this result, we then econometrically analyze survey data on farmers' expectations regarding ACB infestations, to see whether higher areawide Bt deployment leads farmers to expect fewer infestations. We find robust evidence for this effect.

The rest of the paper proceeds as follows: We first present a conceptual model of pest suppression spillovers and feedbacks in the demand for Bt maize, followed by a detailed description of our econometric approach. We then provide a description of the empirical context and the dataset used in the study, before discussing some econometric considerations (vis-a-vis our data). Estimation results are then presented and interpreted. We then discuss implications and limitations of our analysis.

2 Conceptual and econometric models

We first present a conceptual model of how we can expect area-level adoption of a pesticidal crop to determine pest densities (the bioeconomic spillover), and in turn determine individual grower choices about whether to adopt GM varieties. While our model makes a number of simplifications, in the following section describing the study area, we argue that it well characterizes the typical insect pest control environment facing a Philippine maize farmer over the time period in our data. We then translate this conceptual model into an econometric approach, and describe the estimation procedure.

2.1 Conceptual model

Consider a farmer facing the *ex ante* binary choice of whether to plant one of two varieties of a crop: a conventional variety fully susceptible to pest damage or a pesticidal variety that protects the plant from damage and also kills the pest (as is the case with Bt maize). To fix ideas with respect to our application to Bt maize, we refer to the conventional variety as the hybrid (H) and the pesticidal variety as the *Bt* variety. In the model, farmers do not observe pest densities in the coming season, but have expectations about future pest pressure (e.g. based on previous years and on forecasts of environmental conditions).

For simplicity, our conceptual model focuses only on uncertainty with respect to pest densities in the upcoming season. Let $\pi_H(d)$ be the *ex post* profit (crop revenues less costs of seed and other inputs) from the non-Bt hybrid given a pest density of d, and π_{Bt} the *ex post* profit from adopting the pesticidal variety, apart from the price premium for the Bt variety. Assume that $\pi_H' < 0$, i.e. that *ex post* profit from the hybrid variety is decreasing in pest density, and that the pesticidal crop is fully protected against pest damage so that π_{Bt} is independent of pest density. Also, suppose that given an areawide Bt adoption level of $C \in [0,1]$ the *ex ante* cumulative distribution function (CDF) for d is $F(d|C)$, which defines farmer expectations about pest densities d in the upcoming season, conditional on areawide adoption C of the Bt variety. Finally, let w denote the price premium for the Bt variety. Then *ex ante* expected profits for the hybrid and Bt varieties are:

$$\Pi_H(C) \coloneqq \mathbb{E}_d[\pi_H(d)|C] \qquad (1)$$

$$\Pi_{Bt} \coloneqq \mathbb{E}_d[\pi_{Bt} - w|C] = \pi_{Bt} - w$$

where the operator $\mathbb{E}_d[\cdot\,|C]$ emphasizes that we are focusing on uncertainty with regard to pest densities conditional on an assumed level of areawide Bt adoption. The farmer will therefore adopt the Bt variety if $\pi_{Bt} - \Pi_H(C) > w$ and will plant the conventional variety if $\pi_{Bt} - \Pi_H(C) < w$. That is, the farmer will base the decision on the *ex ante* expected profit differential $\Delta\Pi(C) \coloneqq \pi_{Bt} - \Pi_H(C)$, relative to the price premium w of the Bt variety.

A generic way to model a pest suppression effect of areawide adoption in the above framework is to assume that $F(d|C) > F(d|C')$ for all $C > C'$, i.e. the CDF conditional on C' first-order stochastically dominates any CDF conditional on a higher C. Under this assumption, and because $\pi_H(d)$ is strictly decreasing, then $\Pi_H' > 0$ (a basic implication of first-order stochastic dominance). Consequently, the expected profit gain from the Bt variety relative to the hybrid variety is decreasing in areawide adoption, i.e. $\Delta\Pi' < 0$.

This provides an intuitive model of a negative, pest suppression feedback from pesticidal crop adoption. As areawide use of Bt increases, farmers expect decreased pest pressure on their own farms.[3] Equilibrium properties mirror those found with respect to congestion externalities (Bayer and Timmins 2005): If any solution C^* to the equation $\Delta\Pi(C^*) = w$ exists on the interval $[0,1]$, then it is the unique equilibrium of the model, the point at which the marginal farmer is indifferent between adopting Bt or the conventional variety. This equilibrium is stable in the sense that there is an individual incentive to adopt Bt if areawide adoption is below equilibrium, and disincentive to adopt if areawide adoption is above equilibrium. That is, $\Delta\Pi(C) > w$ for all $C < C^*$ and $\Delta\Pi(C) > w$ for all $C > C^*$. Figure 1 illustrates such an equilibrium. If no solution to this equation exists, then $\Delta\Pi(C)$ exceeds w across the whole

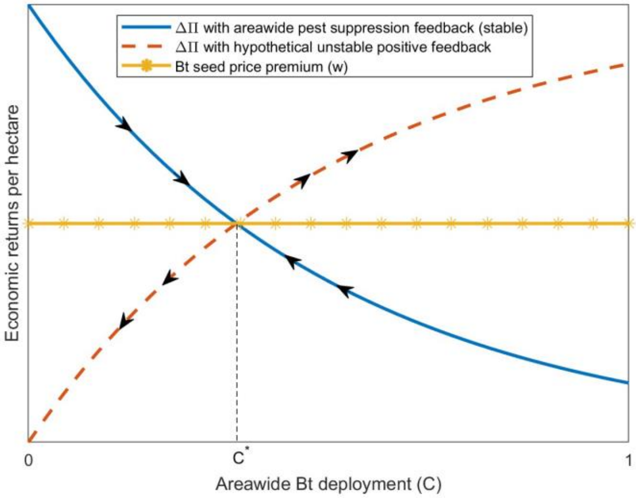

Figure 1

unit interval, in which case full adoption of Bt is the equilibrium, or w exceeds $\Delta\Pi(C)$ across the whole unit interval, in which case the unique equilibrium is no adoption of the Bt variety.

Alternatively, a pest control method could feasibly result in repelling – rather than suppressing – pests from areas where the method is adopted to areas where the method was not yet adopted. In this case CDFs of pest pressure for non-adopters conditional on *high* area-level adoption could stochastically dominate those with lower adoption, ultimately flipping the polarity of the modeled feedback from negative to positive. This would be analogous to an agglomeration externality (Bayer and Timmins 2005). In our context, we hypothesize that a pest suppression feedback is the most relevant for study, rather than repulsion. For Lepidopteran pests like ECB and ACB, Bt crops have a clear suppressing as opposed to repelling effect because they act on the caterpillar larvae, which have limited ability to avoid exposure to the Bt toxins (Hutchison et al. 2010).

Such an areawide pest suppression feedback will also in general reduce the absolute price elasticity of demand for the Bt variety. To see this in a discrete choice model of seed choice, we must extend the above model to allow for heterogeneity or some random component to farmer profits. For exposition assume that the profit differential $\Delta\Pi_i(C)$ for farmer i is $\Delta\Pi_i(C) \coloneqq \Delta\Pi(C) + \epsilon_i$, where ϵ_i is a random component of the farmer returns to Bt-versus-hybrid varieties, with pdf $f(\epsilon_i)$. Then all farmers with ϵ_i such that $\Delta\Pi(C) + \epsilon_i > w$ will adopt the Bt variety, and the resulting demand for the Bt variety is $D_{Bt}(w, C) \coloneqq \int_{w-\Delta\Pi(C)}^{\infty} f(\epsilon_i) d\epsilon_i$.

With the pest suppression feedback and this random component to profits, an equilibrium areawide Bt adoption level C^* now satisfies $D_{Bt}(w, C^*) = C^*$. Applying the Implicit Function Theorem to this equation to derive dC^*/dw when $\Delta\Pi' < 0$ (i.e. areawide pest suppression) and given $f(\cdot) > 0$, we obtain the relation:

$$\left.\frac{\partial D_{Bt}}{\partial w}\right|_{C=C^*} = -f[w - \Delta\Pi(C^*)] < -\frac{f[w-\Delta\Pi(C^*)]}{1-f[w-\Delta\Pi(C^*)]\underbrace{\Delta\Pi'}_{(-)}} = -\left.\frac{\frac{\partial D_{Bt}}{\partial w}}{\frac{\partial D_{Bt}}{\partial C}-1}\right|_{C=C^*} = \frac{dC^*}{dw}\,(< 0) \qquad (2)$$

This relation shows the price elasticity of demand accounting for pest suppression feedbacks is lower in absolute magnitude than the price elasticity ignoring it, i.e. $\left|\frac{dC^*}{dw}\right|\frac{w}{C^*} < \left|\frac{\partial D_{Bt}}{\partial w}\right|\frac{w}{C^*}$. In economic terms, a price change in the Bt variety is met by a countervailing change in pest pressure which attenuates the demand effects of the price change.

2.2 Econometric approach

To empirically evaluate the presence of endogenous feedbacks from Bt seed use, we use an IV method developed by Bayer and Timmins (2007) to estimate a discrete choice econometric random utility model (RUM) with endogenous sorting. We apply this method to model farmers' crop variety choices. Following Ciliberto et al. (2019), who also estimate a discrete choice model of farmers seed variety choices (without endogenous sorting), *ex ante* utility can be interpreted as implicitly containing the expected profit from selecting seed variety j, but may also be related to other factors directly affecting utility, such as farmer preferences specifically regarding genetically modified crops (Useche, Barham and Foltz 2009; Birol, Villalba and Smale 2008).[4]

We specify the *ex ante* utility U_{jih} to the farmer of crop variety j for grower i in area h by partitioning farmer and area-level utility components:

$$U_{jih} = \delta_{jh} + \boldsymbol{\beta}'\boldsymbol{x}_{ji} + \epsilon_{jih} \qquad (3)$$

where δ_{jh} is the area-level effect of variety j on utility, $\boldsymbol{x}_{ji}$ is a vector of farmer-level covariates varying across varieties, $\boldsymbol{\beta}$ is an associated vector of regression coefficients, and ϵ_{jih} is a random utility component. The area-level effect is decomposed as:

$$\delta_{jh} = \bar{\delta}_j - \eta p_{jh} + \alpha Bt_j C_h + \xi_{jh} \qquad (4)$$

where $\bar{\delta}_j$ is a variety-specific constant, p_{jh} is the price of variety j in area h with associated marginal utility η, C_h is the fraction of growers in area h employing varieties with the Bt trait, Bt_j is a dummy variable indicating whether variety j possesses the Bt trait, and ξ_{jh} is an area-level residual. We aim to estimate the utility parameters α, $\boldsymbol{\beta}$, η and, $\bar{\delta}_j$.

The parameter we focus on is the spillover effect, α, of areawide Bt use, C_h. Note that areawide Bt use C_h is interacted with Bt_j in equation (4) for both theoretical and mechanical reasons. The simple theory in section 2.1 implies that greater areawide use of Bt decreases the relative utility ($\partial U_{jih}\ /\partial C_h < 0$) only for those j with the Bt trait ($Bt_j = 1$), yielding the hypothesis that $\alpha < 0$. Mechanically, C_h cannot enter alone as a covariate in (4) because this variable does not vary over alternatives j, and it is only differences between alternatives that identify preferences in a RUM (Train 2009). Interacting C_h with Bt_j produces necessary variation over j.

Assuming the farm-level random utility component ϵ_{jih} in (3) is iid extreme value, we obtain the fixed effects conditional logit model for the probability P_{jih} of grower i selecting variety j in area h:

$$P_{jih}(\boldsymbol{\beta}, \boldsymbol{\delta}_h) = \frac{\exp\{\boldsymbol{\beta}'\boldsymbol{x_{ji}} + \delta_{jh}\}}{\sum_{k\in h}\exp\{\boldsymbol{\beta}'\boldsymbol{x_{ki}} + \delta_{kh}\}} \tag{5}$$

where "$k \in h$" is short-hand to indicate the denominator in (5) sums over all the varieties k available in area h (in our application, areas are village×year).

The standard approach to estimating this model is via a two-stage procedure. In the first stage, estimates $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\delta}}_h \coloneqq \left(\delta_{jh}\right)_{j=1,\dots,J}$ are obtained from maximum-likelihood (ML) estimation combined with a contraction mapping algorithm from Berry et al. (1995). In the second stage, the estimated $\hat{\delta}_{jh}$ serve as dependent variables in a linear regression on observable variety-specific factors varying at the area level, using the decomposition in (4) and treating the unobserved area-level component ξ_{jh} as a regression error. If the explanatory variables in (4) are orthogonal to ξ_{jh}, then this second-stage can be estimated consistently with OLS or other standard panel data methods (Murdock 2006).

However, with endogenous sorting, area-level explanatory variables in the second stage include the area-level adoption of Bt. This creates an obvious endogeneity problem, since correlation in areawide unobservables likely implies $\mathbb{E}(\xi_{jh}|C_h) \neq 0$. As Timmins and Murdock (2007) point out, naïve OLS of (4) tends to bias estimates of α upwards, because of unobserved area-level factors giving rise to correlated choices. Examples of such unobserved areawide correlation in the present context include (i) unobserved agronomic characteristics of different varieties that make them more or less suited for a given area, (ii) unobserved expected profit and utility effects of other inputs (e.g. fertilizer, pesticides, or labor) that are altered by adoption of Bt-versus-alternative maize varieties (Afidchao et al. 2013), and (iii) local ecological conditions favoring pests that may increase relative demand for pesticidal varieties.

To specifically account for endogenous sorting in the econometric analysis, Bayer and Timmins (2007) propose an IV for the market shares σ_{jh}. In their originally intended application to urban economics, j indexes geographic location (rather than seed variety) and h indexes market. In the context of geographic sorting models, they propose as an IV a function $f(X_j, X_{-j})$ of "the attributes [$X_{jh} \coloneqq (x_{jih})_{i=1,\ldots,n_h}$] of location j and the exogenous attributes [$X_{-j} \coloneqq (x_{-jih})_{i=1,\ldots,n_h}$] of *other* locations [$-j$]" (pp. 361, emphasis added). In practice, this function is the conditional logit predicted probability, $f(X_{jh}, X_{-jh}) \coloneqq n_h^{-1} \sum_{i \in h} \frac{\exp \boldsymbol{\beta}' \boldsymbol{x}_{jih}}{\sum_{k \in h} \exp \boldsymbol{\beta}' \boldsymbol{x}_{kih}}$. Bayer and Timmins demonstrate the validity and performance of this estimator using Monte Carlo analysis, and a number of subsequent studies have applied this method to domains ranging from congestion in fishing sites (Timmins and Murdock 2007; Hicks et al. 2012), nonmarginal valuation of climate amenities (Timmins 2007), to urban crime (Bernasco et al. 2017).

Bayer and Timmins (2007, p. 365) explain that identification using their instrument is provided by exogenous variation in "effective choice sets" – that is, not only variation between areas in the available alternatives (seed varieties in our application), but also exogenous variation in the relative utility those alternatives convey. In our application this means that exogenous, between-area differences in the utility conveyed by seed varieties can generate variation in the effective choice set. For example, more remote farmers might find it more costly to access agricultural inputs such a pesticides and thus find the built-in pest control services of Bt seed varieties relatively more attractive. In this example, we would then expect relatively greater exogenous utility from the Bt trait in areas characterized by relatively remote farms. Interacting an indicator for farm remoteness with the variety-specific Bt trait would allow for such observable preference heterogeneity to generate effective choice set variation. Similar conceptual examples could be constructed to illustrate how observable heterogeneity in preferences for the herbicide tolerance (HT) trait (e.g. via farm terrain) could also generate effective choice set variation.

To implement this identification strategy, we include an array of exogenous farm(er) characteristics interacted with variety-specific dummy variables in the discrete choice RUM (since discrete-choice RUMS require such characteristics to interact with alternative-specific variables). Our IV for areawide Bt deployment therefore takes the following form in our application:

$$C_h^{IV} := \sum\nolimits_{j\in h} \frac{Bt_j}{n_h} \sum_{i\in h} \frac{\exp\{\hat{\beta} x_{jih} - \tilde{\eta} p_{jh}\}}{\sum_{k\in h} \exp\{\hat{\beta} x_{kih} - \tilde{\eta} p_{kh}\}} \tag{6}$$

where $\tilde{\eta}$ is an initial guess of the price coefficient obtained by regressing $\hat{\delta}_{jh}$ on p_{jh} without areawide feedbacks (Timmins and Murdock 2007; Hicks et al. 2012; Bernasco et al. 2017).

One potential limitation of the above methodology is the conditional logit model's assumption of the 'independence of irrelevant alternatives' (IIA) (McFadden 1978), which would imply that introduction of the stacked HT-Bt variety would draw farmer demand in equal proportions away from the other available varieties (the single-trait Bt and non-GM hybrid maize). Although our inclusion of area-level fixed effects in (3) relaxes the IIA assumption at the area level, as a robustness check we also estimate a mixed logit model with area-level fixed effects (see Supplementary Material). We do not reject the more parsimonious conditional logit model.

As an additional investigation of bioeconomic feedbacks, we investigate whether results from our RUM are consistent with other indicators of areawide pest suppression. Areawide pest suppression from Bt implies that higher areawide deployment of Bt decreases expected pest pressure. While lacking pest monitoring and entomological data, our surveys elicited a binary indicator b_{ih} of whether farmer i in village-year h expects ACB infestation. To test for areawide ACB suppression, we therefore estimate the following probit regression:

$$\mathbb{E}[b_{ih} | C_h, c_{ih}, X_{ih}] = \Phi(\beta_0 + \beta_C C_h + \beta_c c_{ih} + \boldsymbol{\beta}'_X \boldsymbol{X}_{ih}) \tag{7}$$

where c_{ih} is an indicator of whether farmer i plants a Bt variety (single trait or stacked), $\boldsymbol{X}_{ih}$ is a vector of control variables, $\Phi(\cdot)$ is the standard normal CDF and the β's are regression coefficients to be estimated. To allow c_{ih} to be endogenous, we estimate (7) using a full-information ML (FIML) bivariate probit regression (see Supplementary Material for details).

3 Study context and data

We apply the above econometric framework using data from surveys of Filipino maize growers. Maize is the second most important crop in the Philippines after rice, with approximately one-third of Filipino farmers (~1.8 million) depending on maize as their major source of livelihood. Yellow maize, which accounts for about 60% of total maize production (white maize accounts for the rest), is the type considered in this study. Maize growing in the Philippines is typically rain-fed in lowland, upland, and rolling-to-hilly agro-ecological zones of the country. There are two cropping seasons per year: wet season cropping (usually from March/April to August) and dry season cropping (from November to February). Most maize farmers in the Philippines are small, semi-subsistence farmers with an average farm size ranging from less than a hectare to about 4 hectares (Mendoza and Rosegrant 1995; Gerpacio et al. 2004).

The most destructive pest in the major maize producing regions of the Philippines is ACB (Morallo-Rejesus, Belen G. Punzalan 2002; Gerpacio et al. 2004; Afidchao et al. 2013). Like its European relative, ACB larvae damage all parts of the maize plant in feeding, before metamorphosing into moths, which can disperse widely (Nafus and Schreiner 1991; Shirai 1998). Historically, ACB infestation has occurred yearly, with pest pressure being roughly constant or increasing over time. Farmers report that yield losses from this pest range from 20% to 80%. According to Gerpacio et al. (2004), although ACB is a major pest in the country, insecticide application has been moderate compared to other countries in Asia. Insecticide application for control of ACB is difficult to effectively implement, often not economical, can interfere with beneficial parasitoids, and can have adverse health and environmental effects

(Nafus and Schreiner 1991; PestNet 2017). In the Philippines, insecticide applications for ACB have been uncommon (Nafus and Schreiner 1991; Yorobe and Quicoy 2006).

Given ACB's dominance as the major insect pest for maize in the country, the agricultural sector was naturally interested in Bt maize varieties as a means of control. As with ECB, Bt maize is highly effective at suppressing ACB larvae (Afidchao et al. 2013).[5] In December 2002, after extensive field trials, the Philippine Department of Agriculture (DA) provided regulations for the commercial use of GM crops, including Bt maize (specifically Monsanto's YieldgardTM 818 and 838). In the first year of its commercial availability, 2002, Bt maize was grown in only 1% of the total area planted with maize – on about 230,000 hectares. In 2008, about 12.8% of maize planted was Bt, and in 2009 this increased to 19%, or about 500,000 hectares. Apart from Monsanto, Pioneer Hi-Bred (since 2003) and Syngenta (since 2005) sell Bt maize seeds in the Philippines.

The data used in this study come from the International Food Policy Research Institute (IFPRI) maize surveys for crop years 2007/2008 and 2010/2011 in the Philippines. The data represent a panel where 278 of the farmers in the 2007 cycle were retained into 2010. Data collected in the survey included information on maize farming systems and environment, inputs and outputs, costs and revenues, marketing environment, and other factors related to Bt maize cultivation were collected (i.e., subjective perceptions about the technology). Actual data collection was implemented through face-to-face interviews using pre-tested questionnaires.

The survey was confined to the provinces of Isabela and South Cotabato, both major maize-producing provinces with a high, sustained level of Bt crop deployment. The non-Bt farmers in our data are strictly hybrid maize users, and there were no observations in the data of farmers using traditional, open-pollinated varieties. This uniformity in the non-Bt group allows for a useful baseline to compare the performance difference between Bt maize relative to a more homogenous population of non-Bt farmers (i.e. hybrid maize users only). Seventeen top maize-producing villages ('barangays') were selected for surveying from these two provinces. Survey sampling proceeded by obtaining lists of farms from each village, and randomly selecting a fixed proportion of farms for surveying.

A total of 468 farmers were interviewed in the 2007/2008 round and 278 of those farmers were also interviewed in the 2010/2011 round of data collection. After dropping farmers with missing and inconsistent information, a total of 683 total observations across both survey years. For the purposes of this analysis, we furthermore exclude villages with fewer than eight growers, due to the difficulties of estimating the δ_{jh}'s in (5) with such small area-level sample sizes. In retained villages, we also restrict econometric analysis presented here to the balanced panel of 261 growers present in both the 2007 and 2011 surveys. We focus on the balanced panel because of additional information that was collected in the 2011 survey and which we use in the analysis here, such as the distance of the farm to the nearest road.[6]

Table 1 summarizes the adoption shares for the different seed types by village (corresponding to the σ_{jh} in section 2.2). From this we can quickly see a number of patterns. First, there is significant heterogeneity in GM crop adoption between villages and years. Second, between 2007 and 2011 there was a significant shift to GM varieties, specifically to the stacked trait variety. In particular 100% of the sampled farmers in five of the 11 villages in 2011 chose the stacked-trait variety; this evidently high demand both poses complications and offers some identifying variation for our proposed econometric approach.

To estimate the choice models used in this study, we require subsets of variables that differ over area, individual and variety. Identification requirements for these variables are that they should be exogenous to both individual choices and area-level adoption of GM varieties. Table 2 summarizes the grower-level variables used in this analysis. At the individual level, we include individual growers' distances to the nearest seed supply source and nearest road in the first-stage estimation, following Sanglestsawai et al.'s (2014) study of the yield effects of Bt adoption in the Philippines using the 2007 survey data. We also include a measure of farmer experience – the number of years farming maize (as of 2007) – and basic indicators of the farm terrain.

While we do not observe pest densities, we do use in this analysis survey data on farmer expectations about the future ACB infestations. Table 2 also shows the mean and standard deviations for responses to the survey question:

> *In using this variety [of seed selected by the farmer], do you expect corn borer infestation? (Yes/No)*

We employ responses to this question as the pest infestation indicator in regression equation (7). As noted above, this indicator is clearly endogenous with seed choice. Table 2 shows that perceived pest infestation risk exhibits proportionally greater between-village than within-village variation, more than any of the other variable in this table. This suggests a high within-village correlation of this variable and an important areawide component to perceived pest infestation risks.

Lastly, to obtain variety-specific prices which vary over villages and years for the RUM in (3) and (4), we follow Ciliberto et al. (2019) in their discrete choice model of seed choice and compute the average price for each maize variety in the dataset for each area. Like in Ciliberto et al. farm-level seed prices are only observed for purchased varieties, and so we regress the survey-elicited price φ_{ivt} that farmer i paid for their seed in village v, year t on village fixed effects interacted with the seed type planted by the farmer and a year dummy.

$$\varphi_{ivt} = \sum_{j} (\theta_{jv} + \theta_{jt}) c_{ijt} + \upsilon_{ivt} \tag{8}$$

where c_{ijt} indicates which variety j farm i purchased in year t, the θ's are regression coefficients to be estimated and υ_{ivt} is the residual. After estimating (8) via OLS, we use predictions from this regression to obtain area-level prices, where an "area" is defined here and throughout as a year-village combination $h = (v, t)$, so that $p_{jh} = \hat{\theta}_{jv} + \hat{\theta}_{jt}$.[7] Table 3 summarizes these computed variety-specific prices. The price premium for Bt single-trait in 2007 is 62% that of the mean conventional hybrid price, declining to 41% in 2011. The premium for the stacked variety is 65% of the mean hybrid seed price in 2011. The price of the hybrid variety increased by an average of 48% between 2007 and 2011. These relative premiums for single-trait Bt and stacked trait varieties are roughly in line with those reported by Ciliberto et al. (2019, Table 3) for the U.S. corn seed market. The price premium differential is largely expected, e.g. given the large regulatory costs involved in getting varieties with genetically-modified traits approved by country governments (Smart, Blum and Wesseler 2017). Given that the costs of Bt seed were estimated at that time to amount to around a fifth of Philippine maize growers' input costs (Afidchao et al. 2013), these premiums can be expected to comprise an important consideration in their seed choices.

4 Econometric estimation and specification

The most significant complication to implementing our econometric approach with these data is the presence of some 0% and 100% village-level adoption shares for 2011, which causes estimated $\hat{\delta}_{jh}$'s in these cases to converge to negative or positive infinity. To deal with this issue, in addition to an IV quantile regression (IVQR) used by Timmins and Murdock (2007) for this same purpose, we estimate an IV Tobit in the second stage regression. Whereas the IVQR treats the 0% or 100% village-level adoption as outlier observations, the IV Tobit more appropriately treats them as censored observations. The censoring in this application results from being unable to observe finite $\hat{\delta}_{jh}$'s in cases where the finite survey sample produces no variation in choices within these areas. The details of how we implement this approach and evaluate its validity are described in the Supplementary Material.

Another econometric issue for estimating the RUM specified in (3) and (4) is the potential for seed price endogeneity (Ciliberto et al. 2019). For example, within-area market power might permit seed producers to increase prices to capture rent, in a way that varies systematically across local geographies or between years (e.g. due to the 2007/2008 world food price crisis, as a reviewer noted). This concern is somewhat alleviated because the logic of RUMs implies only between-variety differences $\left(p_{jh} - p_{kh}\right)$ in seed prices affect choices in these models. Any endogenous markups to price would have to differ by variety *and* by area to contaminate our model with price endogeneity. For example, if an omitted factor was driving endogenous variation in GM seed prices but this variation was constant across varieties, then it would have no effect on the identification of a discrete choice RUM. Alternatively, if there was endogenous variation in GM seed price premiums that was constant across areas, it would be picked up by the variety-specific constants ($\bar{\delta}_j$ in eq. 4), which we make no attempt to economically interpret in this manuscript (e.g. for an overall economic valuation of GM maize, which is a central aim of Ciliberto et al.'s analysis). Nevertheless, heterogeneous GM-specific premiums remain possible. Ciliberto et al. (2019) address price endogeneity in the U.S. seed market by instrumenting with the total number of competing products in local markets. We cannot execute this method in our data, because in any given year the number of competing products is constant across villages.

We therefore adopt a two-part approach to address the potential for price endogeneity vis-à-vis our primary empirical aims. We use our knowledge of the Philippine maize seed market and a statistical check for systematic variation in prices. As noted in Section 3 above, the seed brands available in the villages in our data did not change over the course of the dataset. And as noted above, single trait Bt was uniformly available in the sampled villages in 2007, and both the single trait and stacked varieties were uniformly available in 2011. This uniformity means that we would not expect market power to be differentially exercised heterogeneously across villages, which would therefore not empirically generate price endogeneity.

We also consider potential market power at the seed retailer level: On this point, our understanding is that there were no significant institutional barriers to entry for sellers in the area-level retail markets in the Philippines. However, one possibility is that the size of the area-level seed markets limited entry and affected market power (Campbell and Hopenhayn 2005; Melitz and Ottaviano 2008). To investigate this, we examine whether there is a relationship between p_{jh} and measures of area-level market size (elicited in our survey). The Supplementary Material provides details on this test, which cannot statistically reject the null hypothesis of no such relationship.

5 Results

Table 4 shows the first-stage conditional logit models, with and without area-level fixed effects. For our purposes the important takeaway from this table is that the set of farm-level covariates, taken as a whole, have statistically significant explanatory power over seed choice (as seen in the significant Wald χ^2 statistics in the table). In the baseline conditional logit regressions without area-level fixed effects (first two columns of table 4), a farm's distance to the nearest seed source and indicators of farm terrain appear to have the most explanatory power for use of the GM seed varieties. As in Sanglestsawai et al. (2014), distance to nearest seed source appears in these columns to have a counterintuitive effect on use of the single-trait Bt variety, with farms farther from their nearest seed supplier evidently more likely to purchase the single-trait Bt seed. However, the counterintuitive effect of seed supplier distance on single-trait Bt use becomes insignificant when area-level fixed effects are included (second and fourth columns of table 4).

The farm's distance to the nearest road also appears to significantly explain demand for the single-trait Bt variety (Table 4). The positive sign of the estimated coefficient, in all specifications, implies more remote farms (i.e. those less connected to transportation networks) are more likely to use the single-trait Bt variety (as well as the stacked trait variety, though none of these coefficients are statistically significant). This patterns appears even stronger when area-level fixed effects are included in the regression (in terms of statistical significance; recall that the coefficient magnitudes in RUMs cannot be directly compared between specifications). Multiple explanations could accommodate this result: More remote farms may find it more costly to access local labor markets, and be using the Bt and herbicide-tolerant varieties to reduce hired labor inputs in pre-harvest pest control (e.g., detasselling) and weeding activities (Felkl 1988a and 1988b; Gouse et al. 2016; Connor 2017). Areawide pest suppression may also play a role: More remote farms may also enjoy fewer benefits of areawide pest suppression from neighbors' use of Bt seed, thereby increasing remote farms' own incentive to use these varieties, *ceteris paribus*. Alternatively, more remote farmers may find it more costly to access and reactively apply topical insecticides upon pest outbreaks, and thus find the Bt trait relatively more desirable as a means of ACB control. This latter hypothesis could also explain why distance to roads has a smaller and insignificant effect on utility from the stacked variety, since access to herbicides is important to benefit from the HT trait in this variety.

The dummy variable indicators for terrain, despite their coarseness, show explanatory power and mostly intuitive relationships with seed choices in table 4. Farms with "rolling terrain" generally appear more likely to use the GM varieties over the hybrid. This could be explained by ecological conditions on such terrain that favor ACB and weeds. Afidchao et al. (2013) find that ACB damage on maize in the Philippines is positively correlated with distance away from rivers and floodplains. "Hilly/mountainous" terrain, meanwhile, can limit potential yield and increase farming costs, limiting incentives for farmers to invest in the extra price premia for more productive varieties.

The seed price coefficient in the base conditional logit model is of the expected sign, though only significant at the 10% level. Seed price is omitted from the fixed effects conditional logit model, because as an area-level variable it is contained within the estimated area-level fixed effects (eq. 4), and thus is included in the second stage regressions (table 5). The seed price coefficient is always negative and significant in these regressions (in all but one model, at <1% levels).

The second-stage regression estimates in table 5 exhibit intuitive patterns and appear to confirm our bioeconomic prediction. Across all of the specifications in table 5, we find a statistically significant negative feedback effect of areawide Bt deployment on utility from these varieties in the IV regressions (columns 3 and 8). Moreover, comparing the naïve OLS model (column 1) with the IV models (columns 3-5), we see as expected that ignoring endogeneity of the feedback results in a smaller magnitude (though still negative) feedback effect. (The magnitudes of the coefficients are comparable across columns, since the same fixed effects from the first-stage logit are used as dependent variables throughout table 5.) Our preferred specification, the IV Tobit in column 5 that allows for endogeneity and censoring of the fixed effects, appears to be conservative both in the estimated relative magnitude (discussed below) and statistical precision of the feedback effect, compared to the IV and IVQR models. In terms of IV performance, we confirm the Bayer and Timmins instrument appears to have sufficient power, with an F-statistic = 11 yielded by a linear regression of observed area-level Bt shares on the IV. Without additional structural assumptions, statistical tests of exogeneity of the instrument are not possible, since this IV system is not over-identified.

The estimated coefficients in table 5 are marginal utilities and preclude direct economic interpretation of magnitudes (although they are comparable across the columns). Two relevant economic quantities can be computed from the estimated coefficients. The first is the ratio between the areawide feedback coefficient and the price coefficient, which can be interpreted as the equivalent variation in utility between a marginal change in seed price or a marginal change in areawide Bt deployment. In terms of reduced utility to farmers, this calculation implies a 1% increase in areawide Bt deployment is equivalent to an approximately 1.7% increase in seed prices in the IV and IV Tobit models (t-statistics of 1.74 and 1.42 respectively), and in the IVQR model to a 2.82% increase in prices (t-statistic = 1.81). This contrasts with a much lower equivalent variation estimate of 0.88% estimate implied by the naïve OLS model.

A second quantity of economic interest, as discussed in section 2.1, are price-elasticities of demand for the Bt varieties. Similarly to our theoretical analysis in eq. (2), we apply the Implicit Function Theorem to the estimated conditional logit model with endogenous sorting; the Supplementary Material provides details. We compute average price elasticities of demand for the Bt varieties across areas (table S3 in the Supplementary Material). In the fixed effects conditional logit model ignoring areawide feedbacks, we estimate that that a 1% price increase results in a 1.77% decrease in demand for the Bt varieties (i.e. price-elastic demand). When we account for the estimated areawide feedback (using our preferred IV Tobit model), we estimate that a 1% price increase results in a 0.58% decrease in demand (i.e. price-inelastic demand).

Turning to the question of whether the above evidence for endogenous sorting is arising due to a bioeconomic feedback from areawide pest suppression, table 6 shows results of the FIML model described at the end of section 2.2 and in the Supplementary Material. We find results highly consistent with our bioeconomic hypothesis. Greater areawide Bt deployment is strongly associated with a significantly reduced perceived likelihood of infestation. Table 6 reports marginal effects. For example, using our preferred specification in the last column of table 6, a 10% increase in areawide Bt deployment is estimated to be associated with a minimum 10.8% reduction in the likelihood that the farmer indicates expecting ACB infestation. This marginal effect is highly robust across specifications controlling for endogeneity and village-level fixed effects.

6 Conclusions

Bioeconomic feedbacks associated with pest control have important implications for agroecological systems. In addition to negative environmental externalities associated with chemical pesticides and the open-access resource issues associated with pesticide resistance, we draw attention here to the positive externalities associated with areawide pest suppression spillovers. While previous entomological research has shown these spillovers to be biologically significant, our econometric analysis is the first to empirically show the potential economic significance of these spillovers, in terms of affecting farmers' demand for pest control technologies. In the presence of pest suppression spillovers from Bt crops, farmers who choose not to plant such crops initially are more likely to continue doing so, as they enjoy the spillover benefits of neighboring farms' use of Bt crops. Indeed, prior media reports in the U.S. have suggested that "farmers are getting savvier about gene shopping" (WSJ 2016), for example avoiding paying the extra technology fee associated with Bt traits in maize targeting the Western corn rootworm, due to generally low perceived risks from that pest in the U.S. in recent years.

Beyond Bt crops, our endogenous sorting approach could be adapted for empirically analyzing other possible bioeconomic feedbacks in the control of pests, other bioinvasions and transmissible diseases. As reviewed at the outset of this paper, previous applications of the instrumental variables strategy introduced by Bayer and Timmins (2007) have ranged over a variety of topics and data structures. Ours is arguably the first paper to show how this approach can be used to identify explicitly bioeconomic feedbacks. These methods could prove equally flexible for such applications, which could include study of spillovers from vaccination choice (Oster 2016), culling to prevent the spread of animal diseases (Gramig and Wolf 2007), or economic responses to invasive species (Jones 2016).

The econometric approach and application this paper develops is not without limitations. Discussing these limitations and their implications in detail is instructive for understanding common empirical issues that arise in studying bioeconomic feedbacks, and for identifying future research avenues. First, while we highlight the importance of landscape-level bioeconomic feedbacks, we lack geolocation data on farms and fields within the villages surveyed. Future research using such data could model and estimate heterogeneous spillover effects across the landscape, characterize network effects, and corroborate results obtained from alternative analytical treatments of pest control spillovers (e.g. using spatial econometrics, Aglasan 2020).

Another limitation of our application is the relatively narrow variety of seed products and trait combinations in the data, e.g. compared to U.S. maize farming where the number of seed products available in any given year and market can exceed a dozen (or a hundred, depending on how a 'seed product' is defined, Ciliberto et al. 2019). Applications of our framework to contexts with greater variety in seed products (and variation in their availability across geographies) would permit the study of how bioeconomic feedbacks affect the economic value of a wide variety of crop traits. Indeed, Ciliberto et al. (2019) use the same underlying discrete-choice framework used in this paper – with a more flexible and expansive model of farmer choice but without bioeconomic spillovers or feedbacks – to obtain economic valuations of GM traits in maize and soy in the U.S.

An open research question is how accounting for the type of bioeconomic spillovers we identify here, reestimated for the U.S., would affect Ciliberto et al.'s valuations. At a basic level, because our analysis empirically shows that farmers to some extent 'free-ride' on others' adoption of the Bt trait, and because Ciliberto et al.'s valuations are based on estimated farmers' willingness to pay for different traits, one might infer from our findings that Cilberto et al. underestimate valuations of Bt traits. An important caveat to this inference, however, is the evolution of pest resistance to Bt in the U.S. compared to the Philippines (where Bt resistance was relatively low during the period we analyze). With Bt resistance operating analogously to an open-access resource (Ambec and Desquilbet 2012; Brown 2018), its interaction with the 'local public good' of areawide pest suppression from Bt is likely to have complex implications, e.g. for economic valuation and policy. For example, Wan et al. (2012), in finding evidence for areawide pest suppression of pink bollworm within Bt cotton systems in China, argue these pest suppression spillovers may be leveraged to assist Bt resistance management. Alternatively, landscape-level pest pressure of secondary (non-target) pests may increase and encourage further pest control expenditures of Bt growers and their neighbors (Kuosmanen, Pemsl and Wesseler 2006). In terms of agricultural policy, these interactions suggest that a mix of positive and negative incentives is likely appropriate to address the multiple externalities generated by these complex ecological feedbacks (Lefebvre, Langrell and Gomez-y-Paloma 2015).

Another important limitation of this paper's analysis is the inability to disentangle purely behavioral or sociological feedbacks (e.g. peer effects or social learning) from the alleged pest suppression feedback. There are two concerns here: the validity of our econometric results and the suitability of our endogenous sorting approach in future applications to bioeconomic systems. While we cannot rule out potential econometric bias in our results from unmeasured peer effects and behavioral spillovers, we argue these are likely to have a small impact in our application and that any resulting bias is likely to make our conclusions more conservative: Bt crops were available for a number of years and widely deployed in the Philippines prior to the study period, and information about these crops appears to have been disseminated widely. Likewise, the stacked trait variety was deployed between the first and second farmer surveys, and (as shown above) achieved rapid adoption by the time of the second survey. Additionally, to the extent that such behavioral spillovers are present and positive (with farmers being more likely to mimic their neighbors in deploying Bt), they likely bias our negative estimated pest suppression feedback towards zero. This means that the magnitude we estimate on this feedback is likely conservative.

In terms of the suitability of an endogenous sorting approach for future bioeconomic analyses, separating out the behavioral feedbacks requires a dedicated identification strategy on top of the endogenous sorting models we study here. A number of recent papers and works in progress introduce novel strategies using field experiments for identifying peer and network effects in technology adoption (Magnan et al. 2015; Beaman et al. 2018), some using the same discrete choice, random utility framework used here (Dickinson et al. 2018; Guiteras, Levinsohn and Mobarak 2019). Combining such behavioral experiments (or quasi-experiments) with study of the underlying ecology can create more empirically grounded models of bioeconomic systems (Brown 2018).

Our analysis could also benefit from the addition of instrumental measurements on pest density or physical crop damage, to corroborate the areawide pest suppression implied by our analysis of farmer seed choices. This paper addresses the lack of such measurements by citing extensive areawide suppression of the European corn borer (a close relative of ACB) with Bt maize that has been observed in U.S. (Hutchison et al. 2010), and by showing that Filipino maize farmers' perceived ACB infestation risk appears to significantly decrease in response to greater village-level use of Bt. Nevertheless, having direct pest density or damage measurements would undoubtedly improve our approach. Whereas the reader could view this paper as a 'partial information' analysis of endogeneity in farmer demand for Bt maize, the addition of pest density observations could be used for a 'full information,' simultaneous estimation of farmer seed choices and explicitly modeled pest population dynamics. Estimating such a model would facilitate empirically based counterfactual or predictive bioeconomic simulations, e.g. of how pest populations react to farmer responses to changes in pricing of Bt traits or in the bundling of Bt with other seed traits such as herbicide tolerance. The addition of explicit pest density data could also be useful for separating out bioeconomic and previously discussed social learning spillovers.

Tables

Table 1: Maize variety adoption shares and number of surveyed growers by village

		2007			*2011*			
Province	*Village / Barangay*	*Hybrid*	*Bt*	*N*	*Hybrid*	*Bt*	*Stacked*	*N*
Mindanao	Olympog	71%	29%	38	14%	18%	68%	28
	Sinawal	79%	21%	52	65%	27%	8%	26
	Tampakan	73%	27%	70	27%	9%	64%	22
Isabela	Andarayan	30%	70%	10	0%	0%	100%	8
	Bugallon	46%	53%	28	0%	17%	83%	18
	San Pablo	50%	50%	20	0%	0%	100%	14
	Villa Luna	26%	74%	35	0%	20%	80%	20
	Cabaseria 5	29%	71%	92	0%	0%	100%	60
	Dappat	45%	55%	33	0%	0%	100%	22
	San Fernando	28%	72%	36	3%	0%	97%	34
	San Manuel	7%	93%	14	0%	0%	100%	12
	TOTAL	207	221	428	28	21	215	264
		48%	52%		11%	8%	81%	

Table 2. Grower-level characteristics used in the choice models.

	Mean	*Standard deviation*	*Village-level std. dev.*[1]	*Village-level variation (%)*[2]
Years maize farming	22	11	4	36%
Distance to roads (km)	0.5	1.1	0.3	31%
Distance to seed source (km)	6.2	10.2	3.5	34%
Terrain				
Flat	66%	48%	29%	61%
Rolling	21%	40%	17%	42%
Hilly or mountainous	14%	35%	14%	40%
Expect corn borer infestation	45%	50%	38%	76%

Table 2 notes: 1. Standard deviation in village×year-level means, 2. Defined as the standard deviation of area (village×year) means divided by the total standard deviation.

Table 3. Variety-specific, area-level seed prices (Philippine pesos, PHP).

	2007		*2011*	
Variety	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Conventional hybrid	185	32	274	36
Bt single-trait	300	44	386	48
Bt/HT stacked-trait	n/a	n/a	451	42

Table 3 notes: These data are obtained from an OLS regression of seed prices paid by growers on village-level fixed effects interacted with variety-specific dummy variables and an independent time trend. Prices for stacked trait in 2007 are not applicable (n/a) because this variety was not available in that year.

Table 4. First-stage random utility model estimates (conditional logit, see equation 5).

	Conditional logit		*Fixed-effects conditional logit*	
Log(seed price)	-1.071*		[in fixed effect]	
	(0.564)			
Maize variety:	Bt single-trait	Stacked	Bt single-trait	Stacked
×Constant	0.233	2.463***	[in fixed effect]	[in fixed effect]
	(0.385)	(0.530)		
×Distance to seed source	0.0288***	-0.0490**	0.0149	-0.0714*
	(0.0105)	(0.0217)	(0.00967)	(0.0409)
×Rolling terrain	0.865**	2.228***	0.139	1.245*
	(0.342)	(0.733)	(0.320)	(0.730)
×Hilly/mountainous terrain	-0.561	-0.360	-1.005***	-0.875
	(0.344)	(0.446)	(0.352)	(0.640)
×Distance to nearest road	0.244	0.102	0.362**	0.111
	(0.165)	(0.246)	(0.153)	(0.242)
×Years farming maize	0.00197	0.0289	0.00125	0.0149
	(0.0132)	(0.0215)	(0.00781)	(0.0172)
Area fixed effects[#]	No		Yes	
Choice occasions	515		515	
Farmers	261		261	
Deg. Freedom	13		10	
Log-likelihood	-313.6		-220.9	
Wald-χ^2	196.66***		41.11***	
Pseudo-R^2	0.321		0.0575	

Table 4 notes: Robust standard errors clustered at the grower level and in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. [#] Area-level fixed effects model calculated using contraction mapping algorithm (Berry et al. 1995). Area-level coefficients (price and variety-specific constants) are contained within area-level effects. 'Within' pseudo-R^2 calculations in fixed-effect models calculated relative to a null conditional logit model with only area-level fixed effects.

Table 5. Second-stage random utility model estimates (see equation 4).

	OLS		2SLS[a]	IVQR[a,b]	IV Tobit[a,c]
	(1)	(2)	(3)	(4)	(5)
Area Bt fraction		-7.811**	-17.79**	-19.98***	-24.19*
× Bt variety		(3.626)	(7.201)	(4.878)	(13.59)
Log(seed price)	-10.30***	-8.829***	-10.44***	-7.098*	-14.06***
	(2.972)	(2.894)	(3.084)	(4.008)	(4.252)
Bt single trait	4.265**	9.433***	17.81***	16.26***	24.05**
	(1.609)	(2.870)	(5.778)	(4.206)	(11.31)
Stacked variety	11.31***	17.42***	26.38***	29.63***	35.01***
	(2.771)	(4.273)	(6.604)	(5.498)	(12.27)
Constant	54.83***	46.84***	55.62***	39.97*	74.8***
	(16.21)	(15.75)	(16.84)	(21.84)	(23.22)
Areas	22	22	22	22	22
Observations	55	55	55	55	55
(Pseudo-)R^2	0.296	0.362	0.22		0.13

Table 5 notes: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unless otherwise noted, we report jackknife standard errors clustered at the area level and obtained from joint estimation of first-stage (fixed effects conditional logit, Table 4) and second-stage regressions. [a] Area Bt fraction instrumented using Bayer and Timmins instrument. [b] IVQR is an instrumental variable quantile regression, using the quantile treatment effects model of Chernozhukov and Hansen (2005; 2006). Due to invalidity of jackknifed standard errors for quantile regression (Shao and Wu 1989) and complex data structure for bootstrap resampling jointly over the discrete choice first stage and area-level second stage, IVQR standard errors are obtained from bootstrap resampling only over the second-stage data (ignoring first-stage measurement error in δ's).

Table 6. Marginal effects on farmer expecting corn borer infestation (see equation 7).

	Probit			IV Probit (FIML)[a]	
	(1)	(2)	(3)	(4)	(5)
Area-level fraction adopting GM	-0.555***	-0.810***	-1.433***	-1.283***	-1.078***
	(0.0703)	(0.0893)	(0.0860)	(0.210)	(0.194)
Own GM adoption (binary)		0.258***	0.235***	-0.0359	-0.214
		(0.0605)	(0.0536)	(0.218)	(0.131)
Rolling terrain	0.127***	0.116**	0.0917*	0.0935*	0.0880*
	(0.0480)	(0.0468)	(0.0514)	(0.0521)	(0.0495)
Hilly/mountainous	0.0369	0.0589	0.101*	0.0782	0.0539
	(0.0529)	(0.0524)	(0.0589)	(0.0572)	(0.0538)
Years farming	0.00331**	0.00323**	0.00185	0.00185	0.00171
	(0.00150)	(0.00148)	(0.00142)	(0.00180)	(0.00171)
Cross-eq. correl.				0.540	0.795*
				(0.372)	(0.208)
Village fixed effects	No	No	Yes	Yes	Yes
Excluded IVs [a]				All	GM premium
F-stat 1st stage IVs				18.78***	17.31***
Observations	515	515	515	515	515
Farms	261	261	261	261	261
Degrees of freedom	4	5	15	31	29
Log-likelihood	-329.1	-318.3	-270.9	-509.7	-510.7
Pseudo-R2	0.0704	0.101	0.235		

Table 7 Notes: Robust standard errors clustered at grower level in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] FIML IV probit estimated as a correlated bivariate probit system between farmer's expected corn borer infestation and own use of GM maize. Instruments include village-level mean GM seed premium, farm distance to seed source and distance to nearest road.

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Notes

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[1] Certain pest control choices (like use of transgenic Bt crops) not only alter landscape-level pest pressure for the primary (e.g., target) pest, but these choices can also alter landscape-level pest pressure for secondary (e.g., non-target) pests. For example, one would generally expect that landscape-level pest pressure for the primary pest would decrease with Bt corn and then landscape-level pest pressure for the secondary pest (not susceptible to the Bt toxin) may increase (Kuosmanen et al. 2006; Catarino et al. 2015).

[2] Throughout this paper, we use the term *bioeconomic* as an abbreviation for 'coupled biological and economic' (system). This mirrors the term's meaning in the context of fisheries (Clark 2010), although we do not analyze explicit biological data in this paper (beyond farmers' expectations about pest infestation) in the way that harvest data are used for bioeconomic analyses of fisheries.

[3] However, as one reviewer has noted, areawide pest suppression benefits of Bt corn not only depends on the relative share of Bt corn on total corn production area, but also on the share of total corn production relative to the total cropland area. In the Philippines in 2018 (and in 2007 when the first survey we analyze was conducted), corn was the second most important crop after rice (see section 3) (FAOSTAT 2020). Moreover, between 70%-100% of crop acres is planted to corn in the lowland and 35%-100% in the uplands (Gerpacio 2004). Our study areas also have traditionally agricultural landscapes where the proportion of agricultural land to total area ranges from 44% to 60% (Philippine Statistics Authority, 2014). Hence, the relative share of corn in the country and the proportion of agricultural land to total land area supports the existence of potential area-wide pest suppression and indicates that this conceptual model applies to our empirical setting.

[4] Other factors that may influence utility from adoption of Bt seed variety are existing policies regarding refuge requirements and coexistence regulations (Skevas, Fevereiro and Wesseler 2010; Groeneveld, Wesseler and Berentsen 2013). For the study period in this paper, there was a 20% refuge requirement in place in the Philippines (Rodriguez 2014), though there is no reliable information with regards to enforcement and compliance to this directive in the study period. In countries where they are present, Bt refuge mandates or recommendations are often poorly enforced, particularly in areas with relatively small, heterogeneous farms and larger numbers of farmers (Carrière et al. 2020). In addition, note that there are no coexistence policies currently in place in the Philippines (nor were there at the time of the study). Thus, these policy-related factors likely do not play a major role in affecting utility derived from Bt seed adoption. One reviewer also noted the potential role of option values in farmers' seed decisions, e.g., the "sunk" nature of Bt seed purchases vis-à-vis the value of waiting for information about the likely severity of pest infestation in the upcoming season. While we do not address this aspect explicitly in our analysis (i.e. we cannot estimate this option value), it does not change the main implications of our conceptual model in Section 2 (by including this option value as a discount on the expected relative benefits of adopting Bt seed), and can be viewed as being subsumed within our econometric model. See Mbah et al. (2010) for analysis of this dimension of the decision problem in bioinvasions.

[5] Other Bt varieties, expressing proteins for controlling rootworms, were not available in the Philippines over the time period analyzed, because these are not considered major pests of corn there. The only other common non-ACB insect pests of corn in the Philippines are the armyworm and cutworm (Gerpacio et al. 2004; Afidchao et al. 2013), which the available Bt varieties do protect against.

[6] We have also replicated the analysis with the unbalanced panel of farmers, excluding the variables only collected in 2011. The main results of the paper are robust; results are available on request to the authors.

[7] Note that in a departure from Ciliberto et al. (2019), who simply calculate the market-level variety specific averages prices for each variety, we specify village θ_{jv} and time θ_{jt} effects as additively separable. This is specifically because of the 5 villages in 2011 for which we only observe farmers purchasing the stacked variety (Table 1), therefore making estimation of a fully model with village×year fixed effects infeasible. That is, we require imputations for the prices for the Bt single trait and hybrid varieties even in village-years where no one was observed purchasing these varieties.

Supplementary Material

Contents

Tables

Mixed Logit Tests of IIA Assumption

Mixed logit relaxes the IIA assumption by allowing for randomly distributed preference parameters $\boldsymbol{\beta}_i \sim \phi(\boldsymbol{\beta}_i|\widehat{\boldsymbol{\Omega}})$ across decision makers i, where $\phi(\cdot)$ is a probability density function (pdf), typically assumed as we do here to be multivariate normal, and $\widehat{\boldsymbol{\Omega}}$ is a collection of distributional parameters (for a normal pdf, a mean and variance-covariance matrix). The econometric approach described above translates completely to the mixed logit case, integrating the predicted probabilities $P_{jih}(\boldsymbol{\beta}_i, \delta)$ in (5) over the pdf for $\boldsymbol{\beta}_i$. Thus, the area-level predicted shares in the mixed logit model are $\hat{C}_{jh} \equiv n_h^{-1} \sum_{i \in h} \int P_{jih}(\boldsymbol{\beta}_i, \widehat{\boldsymbol{\delta}}_h)\, \phi(\boldsymbol{\beta}_i|\widehat{\boldsymbol{\Omega}}) d\boldsymbol{\beta}_i$, and the logit fixed-effects contraction mapping still holds (Berry, Levinsohn and Pakes 2004). Because mixed logit contains conditional logit as a restricted case, we test whether we can reject the conditional logit restrictions using a likelihood ratio (LR) test. The mixed logit model also makes some use of the panel nature of our data: Farmer i's choices are observed in two separate years, 2007 and 2011, which are treated as distinct areas (h) in this model, and in the mixed logit model each farmer's preference parameters $\boldsymbol{\beta}_i$ are fixed across choice occasions.

Modifying our empirical specification in eq. (3), we also perform specification tests of random (mixed logit) versus fixed parameters (conditional logit) in the first-stage RUM. Our general specification allows for a farm-level random utility effect Δ_{ji} associated with each variety j:[1]

$$U_{jih} = \delta_{jh} + \boldsymbol{\beta}'\boldsymbol{x}_{ji} + \Delta_{ji} + \epsilon_{jih} \tag{S1}$$

with the assumption that $(\Delta_{Bt,i}, \Delta_{Stacked,i})$ are jointly i.i.d. $\mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ and the standard RUM restriction that reference alternative H's random effect is zero ($\Delta_{H,i} = 0$) to ensure identification (Train 2009). In this model, the covariance matrix $\boldsymbol{\Sigma}$ of the random effects is to be estimated in addition to the coefficients in (S1). This model relaxes the IIA assumption by allowing for nonzero off-diagonal elements of $\boldsymbol{\Sigma}$. Further analysis in last two columns of table S2 shows that imposing the restriction that $\operatorname{corr}(\Delta_{Bt,i}, \Delta_{Stacked,i}) = 1$ does not result in the loss of any statistically significant explanatory power (LR test p-value = 0.33). Therefore, our preferred mixed logit specification for first-stage seed choice RUM (last two columns of table S2) assumes a common random effect from either of the GM varieties, with $\Delta_{GM,i} \coloneqq \Delta_{Bt,i} = \Delta_{Stacked,i}$, reducing $\boldsymbol{\Sigma}$ to a single component, s_{GM}.

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[1] Note that the two-year panel rules out fixed effect estimation of Δ_{ji} in a conditional logit model: For any farmer who planted the same variety j in both years, fixed effects estimation yields $\Delta_{ji} = \infty$ (or $\Delta_{ki} = -\infty\ \forall k \neq j$), to ensure that farmer's predicted probability of selecting that variety equaled one, i.e. the observed share of choice occasions they purchased that variety.

Results from the mixed logit estimation suggest that inclusion of area-level fixed effect estimation appears to obviate the need for relaxing IIA using the farm-level mixed logit model. While mixed logit model without area-level fixed effects (second column, table S2) yields a statistically significant estimate of s_{GM}, suggesting the importance of unobserved preference heterogeneity, this additional explanatory power dissipates when area-level fixed effects are included (last column, table S3). An LR test between the mixed and conditional logit models with area-level fixed effects (column 3 of table S2 v. the fixed effects conditional logit model in table 4 of the paper) yields a p-value of 0.24, compared to a p-value of 2.7×10^{-5} from the same test of mixed v. conditional logit *without* area-level fixed effects. These results suggest that accounting for unobserved farm-level heterogeneity in seed preference in these data is less important than accounting for area-level heterogeneity.

Table S1. First-stage seed choice, mixed logit specification tests

	(1)	(2)	(3)
Log(seed price)	-1.214	-1.910**	[in fixed effect]
	(0.850)	(0.837)	
Bt single-trait ×			
Constant	0.488	0.791	[in fixed effect]
	(0.557)	(0.603)	
Distance to seed source	0.0321*	0.0352*	0.0159
	(0.0169)	(0.0186)	(0.0136)
Rolling terrain	0.730*	0.875*	0.158
	(0.418)	(0.469)	(0.367)
Hilly/mountainous terrain	-0.627	-0.650	-1.056***
	(0.440)	(0.493)	(0.390)
Distance to nearest road	0.261*	0.290	0.377***
	(0.155)	(0.177)	(0.139)
Years farming maize	0.00447	0.00331	0.00186
	(0.0156)	(0.0182)	(0.00849)
Stacked variety ×			0.0159
Constant	3.189***	3.404***	[in fixed effect]
	(0.740)	(0.765)	
Distance to seed source	-0.0576	-0.0426	-0.0707*
	(0.0376)	(0.0291)	(0.0379)
Rolling terrain	2.482***	2.312***	1.345
	(0.923)	(0.774)	(0.936)
Hilly/mountainous terrain	-0.0355	-0.120	-0.869
	(0.596)	(0.523)	(0.608)
Distance to nearest road	0.0256	0.0664	0.122
	(0.232)	(0.203)	(0.206)
Years farming maize	0.0398	0.0339	0.0171
	(0.0262)	(0.0225)	(0.0167)
Random parameters[1]			
s_{GM}		1.767***	0.658
		(0.357)	(0.442)
s_{Bt}	1.260***		
	(0.454)		
s_{Stacked}	2.182***		
	(0.650)		
$s_{\text{Bt,Stacked}}$	2.750***		
	(1.040)		
Area fixed effects[2]	No	No	Yes
Choice occasions	515	515	515
Farmers	261	261	261
Deg. Freedom	16	14	11
Log-likelihood	-303.7	-304.8	-220.2
Pseudo-R^2	0.343	0.341	0.0596

Table S2 notes: Robust standard errors clustered at the grower level and in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1. [1] $s_{\mathrm{Bt}}, s_{Stacked}, s_{\mathrm{Bt,Stacked}}$ are the estimated standard deviations and covariance ($s_{\mathrm{Bt,Stacked}}$) from a mixed logit model allowing for separate random components for the Bt-only and Stacked varieties; $s_{\mathrm{GM}}$is the estimated standard deviation in a mixed logit model for a single random component associated with both the GM seed varieties: single trait B or stacked trait. [2]Area-level fixed effects model calculated using contraction mapping algorithm (Berry et al. 1995). Area-level coefficients (price and variety-specific constants) are contained within area-level effects. Pseudo-R^2 calculations in fixed-effect model calculated relative to a null conditional logit model with only area-level fixed effects.

Econometric specification to test for areawide pest suppression

For convenience we reproduce eq. (7) from the published manuscript here:

$$\mathbb{E}[b_{ih}|C_h, c_{ih}, X_{ih}] = \Phi(\beta_0 + \beta_C C_h + \beta_c c_{ih} + \boldsymbol{\beta}'_X \boldsymbol{X}_{ih}) \qquad (7)$$

where c_{ih} is an indicator of whether farmer i plants a Bt variety (single trait or stacked), $\boldsymbol{X}_{ih}$ is a vector of control variables, $\Phi(\cdot)$ is the standard normal CDF and the β's are regression coefficients to be estimated. The hypothesis to test is $\beta_C < 0$. We include own-farm Bt adoption c_{ih} because its obvious correlation with area-level Bt adoption, $C_h = n_h^{-1} \sum_i c_{ih}$, threatens omitted variable bias if excluded from (7). However, inclusion of c_{ih} also poses potential endogeneity concerns. For example, environmental conditions might predispose certain lands to greater pest infestation, in which case farmers on that land might both expect more infestation and exhibit a greater likelihood of using Bt maize. To address endogeneity of c_{ih} (which like b_{ih} is binary), we therefore estimate a full-information maximum likelihood (FIML) bivariate probit regression with b_{ih} and c_{ih} as dependent variables. This models captures endogeneity through the cross-equation correlation in normally distributed residuals associated with each dependent variable (Amemiya 1985). The selection of instruments for c_{ih} is motivated by the RUM in (3) and is described in more detail in subsequent sections. Our expectation in the FIML model is that $\beta_c < 0$ (own-farm Bt adoption causes a reduction in expected pest infestation). As an additional robustness check, we also include village-level fixed effects in (7), in which case identification of β_C rests on within-village variation in C_h between 2007 and 2011.

For this model we must select excludable instruments predicting use of the Bt varieties (c_{ih} in eq. 7), but do not directly predict expected pest infestation (b_{ih}). For this purpose, we use a subset of the farmer-level covariates in our seed choice RUM: price premiums for GM varieties (computed in this regression as the average premium between the Bt and single trait varieties), as well as the farm's distance to the nearest road and the nearest seed source. As shown below (e.g. the F-statistics in table 6), these factors are statistically significant determinants of seed choice, and we argue should satisfy the exclusion assumptions that they not directly affect pest pressure. (In contrast, the other seed choice variables in the RUM – the terrain indicators – we consider as violating the exclusion restrictions.) We investigate robustness of the FIML probit results with respect to subsets of these instruments, finding that the GM seed price premium has nearly the same F-statistic with respect to explaining c_{ih} as compared to all excluded instruments.

The marginal effect of areawide Bt deployment on expected infestation is also robust across specifications, and in fact increases as we account for additional potential sources of bias (moving from left to right in table 6), from omitted variables to endogeneity. In the probit regressions including own-farm use of Bt, the marginal effect of areawide deployment increases, whereas own-farm Bt use exhibits a highly significant positive marginal 'effect.' This result raises obvious concerns about endogeneity described above. When we control for this endogeneity of own-farm Bt use in the FIML models (columns 4-5), using either the full set of instruments or only the GM seed price premium, the estimated marginal effect of own-farm Bt use changes sign as we would expect, though loses statistical significance. A negative marginal effect would be consistent with the own-farm use of Bt varieties reducing perceived ACB infestation risk. In contrast, the positive cross-equation correlation of residuals between perceived infestation risk and Bt use suggests that farmers who *ex ante* perceive greater pest pressure are also more likely to select Bt varieties, although this correlation is only statistically significant in a single specification and only at the 10% level.

Estimating the IV Tobit model for the area-level second stage regression.

We use an IV Tobit to jointly address censoring of the $\hat{\delta}_{jh}$'s and endogeneity of C_h. The logic of censoring the δ's associated with boundary shares is that, because we have finite samples of farmers in each area, the smallest and largest area-level interior shares we can observe with a sample of size n_h are, respectively, n_h^{-1} and $(1 - n_h^{-1})$. And because the predicted shares $\hat{\sigma}_{jh}$ are strictly monotonic in the fixed effects, with $\partial\hat{\sigma}_{jh}/\partial\delta_{jh} > 0$ and $\lim_{\delta_{jh}\to\infty} \hat{\sigma}_{jh} = 1$ (and $\lim_{\delta_{jh}\to-\infty} \hat{\sigma}_{jh} = 0$), then if the true δ_{jh} is large enough (but finite) in magnitude it will yield $\hat{\sigma}_{jh}(\delta_{jh}) > (1 - n_h^{-1})$, i.e. the predicted share at the true parameters is greater than can be measured with a sample size of n_h. This implies the true δ_{jh} is greater than any estimate a size-n_h data sample could produce and makes it more likely we observe $\sigma_{jh} = 1$, in which case we treat $\hat{\delta}_{jh}$ as censored from above. Conversely, if δ_{jh} is negative and so large in magnitude that $\hat{\sigma}_{jh}(\delta_{jh}) < n_h^{-1}$ and we likely observe $\sigma_{jh} = 0$, then we treat $\hat{\delta}_{jh}$ as censored from below.[2]

We implement IV Tobit via limited-information maximum likelihood (LIML), with first-stage linear projection of C_h onto C_h^{IV} inserted into the Tobit regression (Roodman 2011). In theory, for maximal efficiency with the Tobit, the upper and lower censoring bounds should vary by area-level sample sizes n_h^{-1}. However, in practice this makes the censoring bounds not only variable but also dependent on the first-stage estimates $\hat{\boldsymbol{\beta}}'\boldsymbol{x}_{ji}$ in (5). So we instead manually specify the lower and upper bounds for the $\hat{\delta}_{jh}$. Since this uses less information than with variable bounds, this estimator is still consistent but less efficient than IV Tobit with the highest

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or lowest known variable bounds. As compared to a simple linear IV regression or IVQR, the IV Tobit adds these censoring assumptions, and an assumption that the error terms ξ_{jh} in (4) are normally distributed and homoscedastic. Because of these strict assumptions, we perform a conditional moments test on the generalized residual of the Tobit model (Cameron and Trivedi 2005; Pagan and Vella 1989). Retrieving a p-value = 0.35 from this test, we cannot reject the null that the model is correctly specified.[3] We also use jackknife standard errors clustered at the area level for the second stage estimates, resampling and jointly reestimating both estimation stages.

Testing for a relationship between area-level seed prices and market size

The sampling methodology for our survey data provides a convenient measure of market size: the number of sampled maize growers in each village-year (Table 1), which by design was proportional to the number of maize growers in each village's records. Table S2 shows OLS results regression p_{jh} on dummies for seed variety j and area-level sample size n_h, with interactions. These regressions show no systematic relationship between market size, and variety-specific prices, either in absolute terms or in terms of the Bt and Stacked trait premiums. In the model with full interactions between n_h and variety-specific dummy variables, the F-statistic testing the joint significance of the n_h regressors has a p-value = 0.516. While this does not completely rule out price endogeneity in the discrete choice model, these results – coupled with the properties of RUMs and the fact as we see below that the price variable performs as

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[3] The formula used for the generalized residual ϵ_{jh} from the left- and right-censored Tobit model can be found in the replication materials for this paper (available from the authors upon request). The conditional moments test of Pagan and Vella (1989) specifies the null hypothesis $\mathbb{E}\left[\epsilon_{jh}\boldsymbol{z}_{jh}\right] = \mathbf{0}$ for any vector $\boldsymbol{z}_{jh}$ of exogenous variables. We set $\boldsymbol{z}_h$ to include all of the exogenous variables used to estimate the second-stage regressions in Table 5, as well as squares and exponential of the continuous variables and all interactions. We implement the test using generalized method of moments (GMM) with an iteratively computed optimal weighting matrix. Details are in the online replication materials.

expected in regression results – suggest that price endogeneity if present is at least not contaminating the main qualitative results of this paper concerning pest suppression feedbacks.

Table S2. Ordinary least squares regression of seed prices on village-level sample size (n_v).

Dependent: Log(seed price)	*(1)*	*(2)*	*(3)*
Bt	0.362***	0.362***	0.205
	(0.0737)	(0.0744)	(0.148)
Stacked	0.633***	0.632***	0.427**
	(0.0903)	(0.0912)	(0.185)
Village-level sample size (n_v)		-0.000192	-0.00155
		(0.000775)	(0.00120)
Bt x n_v			0.00210
			(0.00170)
Stacked x n_v			0.00279
			(0.00220)
Constant	5.438***	5.453***	5.554***
	(0.0521)	(0.0784)	(0.104)
Observations	55	55	55
Degrees of freedom	3	4	6
R^2	0.510	0.511	0.532
P-value of F-test on n_v regressors		0.806	0.516

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimating the long-run price elasticity of demand with endogenous sorting

Because the probability of planting either of the Bt crops is one minus the probability of planting the hybrid variety, it easiest to derive marginal effects in terms of the predicted probability of planting the hybrid variety. Moreover, we consider the effect of a common price change to both Bt crop varieties, which in the RUM specified in (3) and (4) is equivalent to an opposing change in the price of the hybrid variety p_{Hh}. Combining (3) – (5), and noting that $b_H = 0$ in (4), the predicted probability of adopting the hybrid is:

$$P_{Hih}(p_{Hh}, C_h) = \frac{\exp\{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{Hi}} + \bar{\delta}_H - \eta p_{Hh} + \xi_{Hh}\}}{\sum_{k\in h}\exp\{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ki}} + \bar{\delta}_j - \eta p_{kh} + \alpha b_k C_h + \xi_{jh}\}}$$

Here, we express P_{Hih} as a function of p_{Hh} and C_h, as these are the focal arguments required to derive the net price elasticity.

In our endogenous sorting model, the area-level average probability of planting Bt crops therefore satisfies the following equilibrium equation:

$$C_h = F_h[p_{Hh}, C_h] \coloneqq n_h^{-1}\sum_{i\in h}[1 - P_{Hih}(p_{Hh}, C_h)]$$

This equation provides an implicit function $\hat{C}_h(p_{Hh})$ for the predicted area-level average Bt probability, in terms of the hybrid variety's price p_{Hh} (though any exogenous factor determining seed variety choice could be substituted here for p_{Hh}). The Implicit Function Theorem implies the net marginal effect of p_{Hh} is:

$$\frac{d\hat{C}_h}{dp_{Hh}} = \frac{\frac{\partial F_h}{\partial p_{Hh}}}{\left(1-\frac{\partial F_h}{\partial C_h}\right)} = \frac{-n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial p_{Hh}}}{\left(1+n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial C_h}\right)} \qquad \text{(S1)}$$

Because p_{Hh} is the logarithm of price throughout the manuscript, (S1) is a semi-elasticity, i.e. the net effect of a marginal percentage change in the price of the hybrid variety (or, conversely, an opposing common marginal percentage change in the prices of the Bt varieties) on the area-level average probability of planting either of the Bt varieties. Dividing (S1) through by C_h gives the full elasticity.

The partial derivatives $\frac{\partial P_{Hih}}{\partial p_{Hh}}$ and $\frac{\partial P_{Hih}}{\partial C_h}$ follow from the standard marginal effects formulas for the conditional logit model:

$$\frac{\partial P_{Hih}}{\partial p_{Hh}} = -P_{Hih}(1 - P_{Hih})\eta$$

$$\frac{\partial P_{Hih}}{\partial C_h} = -P_{Hih}(1 - P_{Hih})\alpha$$

When there is no feedback effect, then $\alpha = 0$ and the area-level marginal effect of prices is simply the area-level mean of the partial derivatives, $\frac{d\hat{C}_h}{dp_{Hh}} = -n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial p_{Hh}}$. As such, the divisor $\left(1 + n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial C_h}\right)$ in (A1) embodies the areawide feedback effect. If $\alpha < 0$ (as hypothesized with areawide pest-suppression), then because $P_{Hih} \in (0,1)$ this effect is attenuating, with $\left|\frac{d\hat{C}_h}{dp_{Hh}}\right| < \left|\frac{\partial F_h}{\partial p_{Hh}}\right| = \left|n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial p_{Hh}}\right|$ when $\alpha < 0$ because:

$$n_h^{-1}\sum_{i\in h} P_{Hih}(1 - P_{Hih})\alpha < 0 \qquad \text{if and only if} \qquad \alpha < 0$$

We compute marginal price effects for the naïve OLS model in column (1) of table 5, where $\alpha = 0$ and the price coefficient estimate is $\eta = -10.30$, comparing this to the IV model in column (5) with estimates of $\alpha = -24.19$ and $\eta = -14.06$. (Note that the predicted probabilities P_{Hih} for the marginal effects computation are the same between both the naïve and IV models, as these are estimated in the fixed effects conditional logit first-stage, i.e. table 4)

Table S3 presents the results of this computation. Results imply that a 1% increase in the price of all Bt varieties (or equivalently a 1% decrease in the price of the hybrid variety), yields on average a long-run 0.58% decrease in the average grower's demand for these varieties in the IV model accounting for areawide feedbacks, compared to an estimated 1.77% decrease in the naïve model ignoring this equilibrium feedback. Due to the complex nonlinear formula in equation (S1) and the fact that our estimation method does not produce covariance estimates between the first- and second-stage coefficients, we do not compute standard errors of the mean price elasticities to account for estimation error in the regression coefficients. Instead, given the point estimates of the coefficients, we report summary statistics for the estimated price elasticities over the sample of 22 areas in the data. As with other parts of our analysis, we see significant heterogeneity in the estimated area-level price responses, with some areas with price elasticities in excess of 7% and others with virtually no estimated response to price. The latter tend to correspond to areas where the Bt single-trait and stacked varieties are fully deployed.

Table S3. Estimated Price Elasticities of Demand.

	Model	*Areas (villages x years)*	*Mean*	*Std. Dev.*	*Min*	*Max*
Semi-elasticity	OLS	22	-0.89	1.02	-0.77	> -0.0001
$d\hat{C}_{Bt}/dp$	IV Tobit	22	-0.29	0.89	-0.21	> -0.0001
Elasticity	OLS	22	-1.77	1.75	-9.76	> -0.0001
$\left(d\hat{C}_{Bt}/dp\right)/\hat{C}_{Bt}$	IV Tobit	22	-0.58	0.54	-7.96	> -0.0001

Table S3 notes: dp refers to the differential with respect to a constant logarithmic change to all Bt varieties' prices, equivalent in the RUM to the opposing differential with respect to the logarithm of the hybrid variety's price. OLS and IV Tobit estimates correspond respectively to regression results in columns (1) and (5) of table 5.