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Bioeconomic feedbacks from large-scale adoption of transgenic pesticidal corn in the Philippines

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Abstract

Farmer control of agricultural pests raises the possibility of bioeconomic feedbacks and spillovers, whereby greater aggregate effort exerted on pest control lowers overall pest densities. This in turn decreases individual growers' marginal incentives for pest control. While economists have written theoretically about such feedbacks or modeled it in simulations of bio-invasions, they rarely measure it econometrically. Here we adapt an instrumental variables methodology developed for discrete choice endogenous sorting models in the environmental and urban economics literatures to study bioeconomic feedbacks in pest control. As a methodological innovation, we introduce use of censored regression methods to handle 0% or 100% market shares in hedonic second-stage analysis of fixed effects in discrete choice models. We apply these methods to study area-level adoption and potential feedbacks from individuals' decisions to adopt transgenic Bt corn, using a panel dataset from the Philippines. In a conceptual model, we generate the hypothesis that greater areawide deployment of Bt crops should reduce individual farmers' incentives to use this technology, *ceteris paribus*. Our econometric estimation supports the hypothesis that greater areawide use of Bt attenuates individual incentives to use these varieties. In terms of economic significance, this feedback effect implies a mean long-run price elasticity for the Bt trait 67% lower than that implied by an econometric model ignoring it. Examining whether this estimated feedback relates to areawide pest suppression, we find farmers' expectations about infestation from the main pest targeted by Bt crops are significantly reduced by higher areawide Bt deployment. We conclude by discussing the welfare and yield implications for these areawide bioeconomic feedbacks.

JEL codes: C33, C35, C36, D24, Q12, Q57
Keywords: bioeconomic feedbacks, area-level pest suppression, crop choice, discrete choice econometrics, endogenous sorting

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1 Introduction

Agricultural systems are rife with feedbacks between farmer decisions, their ecological consequences, and economic reactions to these consequences (Janssen and van Ittersum 2007). The control of crop pests provides a particularly salient example of these feedbacks. Credible estimates put global crop losses due to pests at roughly a quarter (Oerke 2006; Culliney 2014), and fast pest population dynamics make feedbacks between farmers' control efforts and pest population manifest on relatively short timescales (Lee et al. 2012). Pest control feedbacks also relate to technology adoption. New agricultural technologies often focus on pest control, including all of the widely adopted genetically modified (GM) crops. The decisions of individual farmers about which pest control measures to deploy, for example whether to adopt a given genetically engineered crop, likely have spillover effects on pest pressure over the entire landscape, potentially affecting the incentives for pest control facing other growers in the area (Ayer 1997; Hutchison et al. 2010; Grogan and Goodhue 2012).

Most econometric analysis of spillovers in the context of agricultural technology adoption has focused on behavioral spillovers and peer effects (Songsermsawas et al. 2016; Maertens and Barrett 2013; Foster and Rosenzweig 1995). Less empirical research analyzes how growers respond to bioeconomic spillovers from pest control.[1] This is in spite of the demonstrable economic significance of bioeconomic spillovers. Hutchison et al. (2010) study corn Bt corn adoption in the Mistwestern US, and investigate the areawide effects of the technology on European corn borer (ECB, scientific name *Ostrinia nubilalis*), historically a major corn pest in this region. They show that widespread adoption of Bt corn caused areawide

[1] In their 2010 review paper, Foster and Rosenzweig do briefly discuss the potential for bioeconomic spillovers in agricultural technology adoption, but argue such spillovers are likely to be more relevant for health-related technologies, particularly for infectious disease prevention.

reductions in ECB densities, providing an estimated $4.3 billion worth of pest suppression benefits to *non*-adopters of the Bt varieties, approximately 60% of the overall pest reduction benefits provided by these varieties. A natural conjecture – one that Hutchison et al. (2010) do not analyze – is that individual incentives to adopt the Bt varieties decrease with greater areawide adoption. Given these potentially large spillovers from individual pest suppression decisions, an obvious question for econometric analysis is whether (and how) they feed back into pest control decisions?

This paper introduces an econometric method from the environmental, resource and urban economics literatures used to estimate the feedbacks of spillover effects in endogenous sorting models (Bayer and Timmins 2007; Timmins and Murdock 2007; Klaiber and Phaneuf 2010; Hicks, Horrace and Schnier 2012). Whereas this literature has applied these models to study endogeneity in housing location or recreation site choice, the choice we analyze here is whether to plant Bt crops. In the sorting literature, negative feedbacks between area-level and individual-level decisions are usually referred to as 'congestion' spillovers, whereas positive feedbacks are referred to as 'agglomeration' spillovers. In the context of pest control practices, we demonstrate in a conceptual model that bioeconomic pest suppression feedbacks should manifest like a congestion-like effect.

Of course, the endogeneity created by these feedbacks requires an econometric identification strategy. In the absence of largescale, multilevel randomized controlled experiments, the dominant method for identifying congestion and agglomeration feedbacks is an instrumental variables (IV) technique developed by Bayer and Timmins (2007). This technique utilizes between-area variation in exogenous characteristics and choice sets to instrument for areawide adoption shares, and then uses these instrumented adoption shares as inputs to a random utility model (RUM) of individual adoption choice. Formally, the method consists of a two-stage regression approach. The first stage consists of estimating a discrete choice model with area-alternative fixed effects by, for example, using the contraction mapping algorithm introduced by Berry et al. (1995). The second stage consists of an IV regression of these estimated area-alternative fixed effects on area-level characteristics, including area-level adoption for which an instrument is constructed as described by Bayer and Timmins (2007).

We apply this framework to a two-year panel of corn farmers in the Philippines, across 11 villages, who chose between planting two corn varieties in the first year of data collection and three corn varieties in the second year. As we argue below, this variation in product availability and heterogeneous benefits of these products over time and space help us to identify endogenous spillovers. An additional econometric challenge we face is that in some villages and years, some of the available varieties were never observed to be used by the sampled farmers, which poses complications for the fixed effects discrete choice models we employ. In addition to following the IV quantile regression approach introduced by Timmins and Murdock (2007) for handling this same difficulty, we also introduce the use of an IV Tobit, which we believe more efficiently handles the issue (albeit with additional econometric assumptions, which we test).

The estimation results across regression approaches shows consistent evidence that greater areawide use of GM corn in the Philippines appears to feed back into decreased individual farmer incentives to elect these varieties. Motivated by theory, prior research and additional statistical analysis of farmer perceptions, we hypothesize this effect is most likely due to areawide pest suppression from the Bt traits, which were present in all GM varieties available at the time data were collected. One way to quantify this effect is as an attenuation on the long-run price elasticity of demand on Bt varieties. By 'long-run' we mean, for example, that if the price of Bt varieties decreased, this would have the immediate effect of increasing demand for these products, which could in turn lead to greater areawide pest suppression, feeding back into reduced individual incentives to use these varieties. In our preferred models, we estimate this attenuation effect reduces the average long-run price elasticity by 67%, compared to a naïve econometric model ignoring this feedback. The pest suppression explanation for the feedback we identify supported by our additional econometric finding that, when areawide use of GM corn was high, farmers perceived a significantly lower risk of insect pest infestation, controlling for farmers' own seed choices and other factors.

The general lesson from our findings is the importance of accounting for feedback effects in modeling crop choices, which may have areawide effects when aggregated. Excluding – or naïvely including – spillovers may lead to biased estimation of the economic value of the GM varieties when using revealed preference data. As we discuss at the end of this paper, recognition of this potential bias could be used to better understand discrepancies between micro-level and aggregated econometric analyses of the yield and profit effects of GM crops.

After reviewing the literature, we present a conceptual model of pest suppression spillovers and feedbacks in the context of seed choice, followed by a description of our econometric approach. We then provide a description of the dataset and empirical context, before discussing some econometric considerations vis-a-vis our data and presenting estimation results. We then interpret these results and conclude.

2 Literature review

There have been many studies that have attempted to estimate the benefits of adopting pesticidal crops for farmers and the broader economy (Qaim, Subramanian and Zilberman 2006, Yorobe and Quicoy 2006, Qaim 2010, Barrows, Sexton and Zilberman 2012). These studies have primarily focused on the direct benefits to adopters and financial benefits that result directly from the activities of the farm. However, various pest management practices have been found to be linked to (sometimes negative) bioeconomic externalities. Ayer (1997) in his work on the desirability of internal coordination among stakeholders in agricultural systems points out the existence of unintended insect losses (bees and predators of pests) due to indiscriminate application of global pesticides. Grogan and Goodhue (2012) discuss negative effects of excessive pesticide usage where farmers eventually become more reliant on pesticides as pest predator numbers are also increasingly reduced areawide by application of these pesticides. Recently, economists have also suggested that usefulness of areawide pest management strategies for managing citrus greening (Singerman, Lence and Useche 2017).

Most relevant for our study, Hutchison et. al. (2010) indicate that similar areawide spillovers exist with Bt adoption. In this context though, the population of the target pest itself (instead of non-target predators) is reduced for Bt adopters as well as non-adopters. Hutchison et al. (2010) show benefits of this reduction in pest numbers are experienced to a greater extent by non-adopters who avoid paying the cost of pest management (since Bt seeds are significantly more expensive than non-Bt ones). This reduces incentives to further adopt Bt corn as a means of pest management, creating the potential for endogenous sorting in choice of seed. Subsequent research has shown that areawide pest suppression from Bt maize can spill over to benefit growers of other crops such as vegetables, and can affect farmers' pest control decisions for these crops (Dively et al. 2018).

Estimation of discrete choice models with endogenous sorting has comprised a major research topic in the hedonic valuation literature within environmental and urban economics (Kuminoff, Smith and Timmins 2013). Schelling (1969; 1971) established theoretical foundations for modeling endogenous interactions in discrete choices, illustrating in particular how endogenous segregation in urban housing patterns can emerge from residents' preferences for locating in areas with neighbors similar to themselves. In the parlance of urban economics, this theoretical framework explains *congestion* phenomena, in which the relative utility and consequent demand for a particular alternative (housing location, recreational site, etc.) decreases as others use that alternative, and *agglomeration*, in which the utility of and demand for an alternative is enhanced with others' use of it. Brito et al. (1991) are the first to show how Schelling's theoretical framework can be applied to bioeconomic feedbacks: They show how vaccination against infectious diseases can give rise to congestion-like effects, whereby the incentive to vaccinate decreases as others vaccinate.

Research beginning in the 1990s attempted to apply Schelling's theoretical framework in econometric models. Brock and Durlauf (2001) develop an econometric model of endogenous binary choices, in which identification is provided by functional form assumptions in a random utility model (RUM). Bayer and Timmins (2005; 2007) first analyze equilibrium properties of these models with more than two alternatives and then propose an instrumental variables (IV) strategy for identifying endogenous feedbacks; this is the approach we use here. Bayer and Timmins show in Monte Carlo simulations that their IV method performs well, regardless of distributional assumptions and functional form assumptions, as long as sufficient variation exists in the "effective choice set," which we explain below. Subsequent applications of their IV method in urban and environmental economics have estimated, for example, the value of open space amenities accounting for congestion externalities (Klaiber and Phaneuf, 2010), amenity costs of climate change (Timmins 2007), pollution-induced migration (Banzhaf and Walsh 2008), and agglomeration economies in firm location decisions (Koster et al.2014).

There has also been some application of these methods to study bioeconomic spillovers associated with renewable resource use. Timmins and Murdock (2007) use this method to estimate congestion spillovers in recreational freshwater angling trips to different lakes, using arguably exogenous variation in lake-level average travel costs and other attributes to construct an instrument for site-level congestion. Using a similar approach, Hicks, Horrace and Schnier (2012) apply this method to identify the effects of overcrowding on fishing site choice in the Alaskan commercial flatfish fishery. Both of these papers find that naïve estimation of bioeconomic spillover effects without accounting for endogeneity implies a strong agglomeration effect, whereas their IV models suggest significant congestion effects.

3 Model

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 corn farmer over the time period in our data. With this model, we demonstrate how the bioeconomic spillover could be expected to manifest as a congestion-like effect, which can under some circumstances attenuate demand for Bt crops. We then translate this conceptual model into an econometric approach, and describe the estimation procedure.

3.1 Conceptual model

To show how areawide pest suppression should result in a negative feedback on demand for pest control, 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 corn). To fix ideas with respect to our application to Bt corn, 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 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 $\partial\pi_H/\partial d < 0$, 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:

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

$$\Pi_{Bt} \coloneqq \mathbb{E}_d[\pi_{Bt} - w|C] = \pi_{Bt} - w \tag{2}$$

where the operator $\mathbb{E}_d[\cdot\,|C]$ emphasizes that we are focusing on uncertainty with regard to pest densities conditional on areawide Bt adoption. The farmer will therefore adopt the Bt variety if $\pi_{Bt} - w - \Pi_H(C) > 0$ and will plant the conventional variety if $\pi_{Bt} - w - \Pi_H(C) < 0$. That is, the farmer will base the decision on the *ex ante* expected profit differential $\rho(C) \coloneqq \pi_{Bt} - w - \Pi_H(C)$.

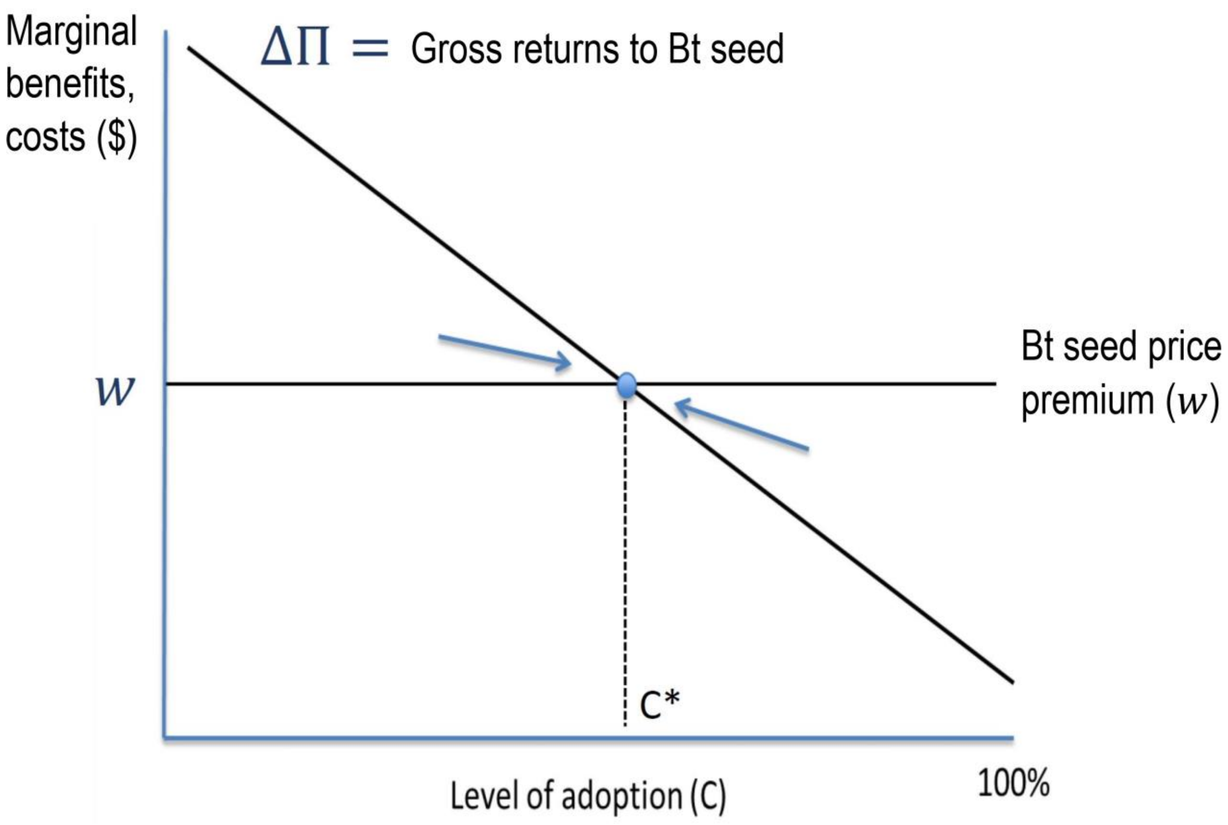
A generic way to model a pest suppression effect of areawide adoption in the above framework is to assume that $F_C(d|C) > F_C(d|C')$ for all $C > C'$, i.e. the CDF conditional on C' first-order stochastically dominates any CDF conditional on a higher C.[2] Under this assumption, and because $\pi_H(d)$ is assumed to be strictly decreasing in d, then $\partial\Pi_H/\partial C > 0$ (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. $\partial\rho/\partial C < 0$.

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. Equilibrium properties are straightforward to derive, and mirror those found with respect to congestion externalities (Bayer and Timmins 2005): If any solution C^* to the equation $\rho(C^*) = 0$ 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, $\rho(C) > 0$ for all $C < C^*$ and $\rho(C) < 0$ for all $C > C^*$. Figure 1 illustrates such an equilibrium, where $\Delta\Pi(C) \coloneqq \Pi_H(C) - \pi_{Bt}$ is the expected profit differential between the Bt and hybrid varieties excluding the Bt seed price premium. If no solution to this equation exists, then $\rho(\cdot)$ is either strictly positive on the unit interval, in which case full adoption of Bt is

[2] 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 conditional on *lower* adoption could first-order stochastically dominate those with higher 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). However, the Bt varieties available in the Philippines over the timeframe analyzed are well known to suppress (rather than repel) ACB larvae, much in the same way that Bt crops in the US were clearly observed to suppress ECB densities at areawide scales (Hutchison et al. 2010). In general, for Lepidopteran pests like ECB and ACB, Bt crops have a suppressing as opposed to repelling effect because they act on the caterpillar larvae, which have limited ability to avoid exposure to the Bt toxins.

the equilibrium, or $\rho(\cdot)$ is strictly negative on the unit interval, in which case the unique equilibrium is full adoption of the hybrid variety.

Figure 1: Illustration of a negative economic feedback from a pest suppression spillover.



3.2 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 discrete choice econometric RUMs with endogenous sorting. We apply this method to model farmers' crop variety choices. Here, *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).

We describe our approach here using the standard conditional logit model of discrete choice with fixed effects, as adopted by Bayer and Timmins. However, their two-stage approach extends to a mixed logit model allowing for farmer heterogeneity in their seed preferences, which we use in specification tests.

In the context of our application, 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:

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

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:

$$\delta_{jh} = \bar{\delta}_j - \eta p_{jh} + \alpha b_j C_h + \xi_{jh} \tag{4}$$

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, b_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, $\bar{\delta}_j$.

In this paper, the parameter of particular interest is the spillover effect, α, of areawide Bt use, C_h. Note that areawide Bt use C_h is interacted with b_j in equation (4) for both theoretical and mechanical reasons. The simple theory in Section 3.1 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 ($b_j = 1$), 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).[3] Interacting C_h with b_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:

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

Note that "$k \in h$" is short-hand to indicate the denominator in (5) sums over all the varieties k available in area (in our application, village×year) h. The standard approach to estimating this model is via a two-stage procedure. In the first stage, estimates $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\delta}}_h \coloneqq (\delta_{jh})_{j=1,\dots,J}$ are obtained from maximum-likelihood estimation (MLE) combined with a contraction mapping algorithm from Berry et al. (1995). This algorithm uses the empirical area-level, variety-specific shares σ_{jh} and an initial guesses of $\hat{\delta}_{jh}$, estimating $\widehat{\boldsymbol{\beta}}$ via MLE conditional on the guess for $\hat{\delta}_{jh}$, computing the predicted area-level, variety-specific shares $\hat{\sigma}_{jh} \coloneqq n_h^{-1} \sum_{i\in h} P_{jih}(\widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\delta}}_h)$, then

[3] It is possible for there to exist nonlinear spillover effects, as has been investigated in other contexts (Hicks et al. 2012). However, our empirical application does not permit enough statistical power to estimate such nonlinearities.

recomputing new area-level fixed effects $\hat{\delta}_{jh}' \coloneqq \hat{\delta}_{jh} + \ln \sigma_{jh} - \ln \hat{\sigma}_{jh}$, and repeating until convergence. Because this algorithm is a contraction mapping, it converges to $\sigma_{jh} = \hat{\sigma}_{jh}$, i.e. the estimated fixed effects $\hat{\delta}_{jh}$ equate the predicted and observed area-level shares.

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 linear panel data regressions (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 the $\hat{\delta}_{jh}$'s are themselves estimated in the first stage to satisfy $\hat{\sigma}_{jh} = \sigma_{jh}$, with $C_h = \sum_{k \in h} b_k \sigma_{kh}$. Econometrically, this endogeneity problem can thus be stated as $\mathbb{E}(\xi_{jh}|C_h) \neq 0$. 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. Such unobserved areawide correlation in preferences in the present context may include unobserved agronomic characteristics of different varieties that make them more or less suited for a given area, as well as areawide marketing of particular 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 context, 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 [$X_{jh} \coloneqq (x_{jih})_{i=1,\dots,n_h}$] of location j and the exogenous attributes [$X_{-j} \coloneqq (x_{-jih})_{i=1,\dots,n_h}$] of *other* locations [$-j$]" (pp.

361, emphasis added). In practice, this function is the conditional logit predicted probability, $f\left(X_{jh}, X_{-jh}\right) \coloneqq n_h^{-1} \sum_{i \in h} \frac{\exp \boldsymbol{\beta}' \boldsymbol{x}_{jih}}{\sum_{k \in h} \exp \boldsymbol{\beta}' \boldsymbol{x}_{kih}}$. Bayer and Timmins demonstrate the validity and performance of this estimator using Monte Carlo analysis. Timmins and Murdock (2007), applying this IV method in their study of endogenous congestion in anglers' choices of recreation sites, explain this instrument's exclusion restrictions further, by noting that there is no reason for the attributes of *other* alternatives to enter directly into the utility for alternative j, "except in the way they impact the share of anglers also choosing j" (pp. 7). Bayer and Timmins (2007, p. 365) also emphasize that another source of identification in $f\left(X_{jh}, X_{-jh}\right)$ is exogenous variation in "effective choice sets," arising either from "data drawn from multiple geographically-distinct markets, a single market observed over many periods, or variation in the orientation of individuals within a single market." Intuitively, the availability of more alternatives in a market or area, *ceteris paribus*, should decrease the probability of selecting any given alternative, and observing area-level responses to such exogenous variation in choice probabilities can be used to infer spillover effects in a RUM. This intuition is captured mathematically when $f\left(X_{jh}, X_{-jh}\right)$ changes with the number of non-chosen alternatives $-j$, as is the case with all discrete choice RUMs including the conditional logit specification.

The choice sets in our application consist of seed varieties, instead of housing locations or recreation sites. In this context, it is orthogonal variation in seed varieties' availability, attributes, and observed heterogeneity in the values of these attributes between areas and over time that drives our identification strategy. We explain each of these empirical sources of identification in turn, and discuss the relative importance in our application.

Variation in the attributes of non-Bt varieties can be used as exogenous information to instrument for Bt adoption shares in the RUM. As long as the basic exogeneity of these attributes

$X_{jih} \coloneqq (x_{ji}, p_{jh})$ is satisfied, i.e. that these attributes X_{jih} are uncorrelated with the error terms ϵ_{jih} and ξ_j – it is reasonable to suppose that these regressors for *other* varieties $(-j)$ should be uncorrelated, in particular, with the error term ξ_j of variety j in (4). As an example, if we assume seed price is exogenous (an issue we take up separately below), then a higher (lower) price of a non-Bt variety, *ceteris paribus*, should increase (decrease) adoption of the Bt variety without directly affecting the utility of the Bt variety, thus satisfying the necessary exclusion restriction for a valid instrument. Empirically, exogenous variation in non-Bt prices over areas and years can then be leveraged to infer how differential adoption of Bt feeds back into area-level spillovers.

This simple example of instrumental variation in relative prices is useful for illustrating how *effective* choice set variation can be generated for a set of seed varieties, i.e. the same variety sold at different prices in different areas can be viewed as different alternatives. In our empirical setting described below, additional effective choice set variation is generated not only by the differences in the actual availability of seed varieties (with an herbicide resistance variety being introduced on top of a conventional hybrid and single-trait Bt in all areas between 2007 and 2011), but also by measureable variation in farmers' relative values placed on the varieties available in their area, as these values relate to observable farmer characteristics. As Bayer and Timmins (2007, p. 364) explain, this source of identification "derives from variation in the orientation [i.e. preferences] of individuals within a single market or among a single set of alternatives."

In our application, this means that observable differences in the mix of farmers between areas can generate variation in the effective choice set. For example, farmers who find it generally more costly to access agricultural inputs (e.g. because of farm remoteness) may find Bt seed varieties relatively more attractive, as a way to prevent more costly pest outbreaks. Thus, we would expect relatively greater exogenous utility from the Bt trait in areas characterized by relatively remote farms. As Bayer and Timmins note (*ibid.*), measuring this kind of instrumental variation requires "the interaction of individual characteristics with locational characteristics [in our application, seed varieties]." So, continuing our example, 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 HT trait (e.g. via farm terrain) could also generate effective choice set variation. To allow for this type of identification, we include an array of exogenous farm(er) characteristics interacted with variety-specific dummy variables in the discrete choice RUM. [4]

Combining these three sources of identification, the IV from Bayer and Timmins therefore takes the following form in our application:

$$\sigma_{jh}^{IV} = \frac{1}{n_h} \sum_{i \in h} \frac{\exp\{\tilde{\beta} x_{jih} - \tilde{\eta} p_{jh}\}}{\sum_{k \in h} \exp\{\tilde{\beta} x_{kih} - \tilde{\eta} p_{kh}\}} \tag{6}$$

where $\tilde{\beta}$, $\tilde{\gamma}$ and $\tilde{\eta}$ are initial 'guesses' of their respective parameters. Bayer and Timmins postulate that any initial guess for these parameters provides consistent estimation, but researchers applying this method generally estimate $\hat{\beta}$ and $\hat{\delta}_{jh}$ via the Berry et al. method, setting $\tilde{\beta} = \hat{\beta}$, and then regressing $\hat{\delta}_{jh}$ on p_{jh} to obtain an initial guess of $\tilde{\eta}$ (Timmins and Murdock

[4] Because inference proceeds on the basis of *differences* in utility in discrete choice RUMs, farm(er)-level factors can *only* be included as explanatory variables if interacted with variety-specific attributes (Train 2009).

2007; Hicks et al. 2012). We follow this approach in our application. In our application, we obtain our instrument for area-level Bt shares, B_h from (6), as $C_h^{IV} \coloneqq \sum_{j \in h} b_j \sigma_{jh}^{IV}$.[5]

To recapitulate, the IV in (6) contains the three sources of identification discussed above. Variation in the attributes of the non-chosen alternatives is reflected mainly by variation in their prices, p_{-jh}. Direct choice set variation is reflected in (6) by variation in the set of alternatives $k \in h$ in each village-year, consisting here of the conventional and single-trait Bt varieties only available in all villages in 2007 and then an additional stacked variety combining Bt and HT traits made available in all villages by 2011. Finally, effective choice set variation through heterogeneous farmer preferences is reflected in x_{ij}, which in our application consists of interactions between farmer-specific characteristics and variety-specific dummies for inclusion in x_{kih} (for *all* varieties k, chosen and nonchosen). It is unclear which of these three identification sources is most dominant in our application; their nonlinear combination in (6) precludes statistical tests which might be used with conventional IV approaches. (We do, however, conduct standard checks for the overall strength of our IV.) For validity of our strategy, it is most important to emphasize we have two sources of identification beyond variation in the availability of seed varieties, since the latter is collinear with time in our data.

One limitation of the above econometric methodology is that the conditional logit model assumes the 'independence of irrelevant alternatives' (IIA) (McFadden 1978). In our application, this assumption could be problematic because of the introduction of the stacked variety to the choice set in 2011. The IIA assumption would maintain that market shares for this variety after its introduction would draw farmer demand equally away from the other available varieties (the

[5] Note that this approach avoids the "forbidden regression" problem, in which a nonlinear prediction of the endogenous regressor is used directly in the last stage. With the Bayer and Timmins approach, we linearly regress C_h on C_h^{IV} in the first-stage of the IV procedure, and then use this linear prediction in the last stage.

single-trait Bt and non-GM hybrid corn). This is clearly an overly strong assumption given that both the GM single-trait and stacked varieties share the Bt feature. However, by estimating area-level fixed effects in the conditional logit model, the IIA assumption is relaxed at the area level, though still assumed to hold at the farmer level.

To investigate the importance of the IIA assumption, we also estimate a more unrestricted mixed logit model, with and without area-level fixed effects. 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 each farmer's preference parameters $\boldsymbol{\beta}_i$ are fixed across choice occasions.

Finally, as an additional test of our theory in section 3.1, we investigate whether results from our RUM are consistent with other indicators of areawide pest pressure and suppression. While we lack pest monitoring and entomological data, we do possess farmer survey data on perceptions of pest pressure. The hypothesis of areawide pest suppression from Bt – specifically, the first-order stochastic dominance assumption in section 3.1 – implies $\partial\mathbb{E}[d|C]/\partial C < 0$, i.e. that higher areawide deployment of Bt leads to lower expected pest pressure. There are two parts to this implication: first, that areawide Bt adoption reduces actual pest density, and second, that these reductions inform farmer subjective expectations to influence seed choice. While we lack entomological measurements on pest density, as discussed above Hutchison et al. (2010) establish the biophysical basis for areawide pest suppression from Bt, and it is likely those same mechanisms apply to the Filipino context of our data (described further below), with extensive, commercial corn farming and Bt crops targeting a pest of the same genus as that analyzed by Hutchison et al. In terms of farmer expectations, our data only provides a binary indicator b_{ih} of whether farmer i in village-year h expects infestation from the pest targeted by Bt varieties. To test whether expected pest pressure responds as expected to area-level Bt deployment, we therefore estimate the following probit regression:

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

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. The hypothesis of interest 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, e.g. with greater expected pest infestation b_{ih} yielding a greater propensity to adopt Bt varieties *ceteris paribus*. To address endogeneity of c_{ih} (which is binary), as a robustness check on a simple probit estimation of (7), we therefore estimate a full-information maximum likelihood (FIML) bivariate probit regression allowing for cross-equation correlation τ in residuals between b_{ih} and c_{ih} (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) and $\tau > 0$ (e.g. higher background pest pressure increases both perceived infestation risk and propensity to plant Bt). 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.

4 Study context and data

We apply the above econometric framework using data from surveys of Filipino corn growers. Corn is the second most important crop in the Philippines after rice, with approximately one-third of Filipino farmers (~1.8 million) depending on corn as their major source of livelihood. Yellow corn, which accounts for about 60% of total corn production (white corn accounts for the rest), is the type considered in this study. Corn 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 corn farmers in the Philippines are small, semi-subsistence farmers with 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 corn producing regions of the Philippines is *Ostrinia furnacalis*, whose common name is Asian corn borer (ACB) (Morallo-Rejesus, Belen G. Punzalan 2002; Gerpacio et al. 2004; Afidchao, Musters and de Snoo 2013). Like ECB, ACB larvae damage all parts of the corn 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. Moreover, Yorobe and Quicoy (2006) suggest insecticide application to control for Asian corn borer has been less appealing due to health and environmental concerns.

Given ACB's dominance as the major insect pest for corn in the country, the agricultural sector was naturally interested in Bt corn varieties as a means of control. As with ECB, Bt corn is highly effective at suppressing ACB larvae (Afidchao et al. 2013).[6] In December 2002, after extensive field trials, the Philippine Department of Agriculture (DA) provided regulations for the commercial use of GM crops, including Bt corn (specifically Monsanto's YieldgardTM 818 and 838). In the first year of its commercial availability, 2002, Bt corn was grown in only 1% of the total area planted with corn – on about 230,000 hectares. In 2008, about 12.8% of corn 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 corn seeds in the Philippines.

The data used in this study come from the International Food Policy Research Institute (IFPRI) corn 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 corn farming systems and environment, inputs and outputs, costs and revenues, marketing environment, and other factors related to Bt corn cultivation were collected (i.e., subjective perceptions about the technology). Actual data collection was implemented through face-to-face interviews using pre-tested questionnaires.

[6] 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.

The survey was confined to the provinces of Isabela and South Cotabato, both major corn-producing provinces with a high, sustained level of Bt crop deployment. The non-Bt farmers in our data are strictly hybrid corn 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 corn relative to a more homogenous population of non-Bt farmers (i.e. hybrid corn users only). Seventeen top corn-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.[7]

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

[7] 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.

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 corn (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 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 $p_{jh} = \hat{\theta}_{jv} + \hat{\theta}_{jt}$.[8] 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.

5 Econometric estimation and specification

Given the data described above, we must address some empirical complications to implement our econometric approach. The most significant challenge to implementing our econometric approach with these data is the presence of 0% and 100% village-level adoption shares for 2011. This poses a challenge to our proposed estimation method, because the

[8] The reason we specify village θ_{jv} and time trend θ_{jt} as additively separable 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 saturated model with θ_{jvt} infeasible, i.e. 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.

estimated $\hat{\delta}_{jh}$'s will converge to negative or positive infinity in these cases (since by design these estimates exactly match predicted village-year seed type shares to their empirical counterparts).

To deal with this problem of boundary adoption shares, we use two alternative approaches: an IV quantile regression (IVQR), following Timmins and Murdock (2007) who deal with this same challenge, and an IV Tobit appraoch. In analyzing the second-stage results, we compare both of these approaches with a simple linear IV regression, as well as naïve OLS ignoring endogenity. Timmins and Murdock (2007) implement the IVQR by first modifying boundary shares σ_{jh} infinitesimally to lie in the interior $(0,1)$ interval, which ensures convergence of the contraction mapping algorithm but yields very large magnitude, though finite, values for the $\hat{\delta}_{jh}$'s associated with boundary shares. In the second stage, Timmins and Murdock then treat the boundary share $\hat{\delta}_{jh}$'s as outliers and use IVQR techniques to address this. We follow that approach here, using the IV quantile treatment effects regression model of Chernozhukov and Hansen (2005; 2006).[9]

The second approach we believe is a novel way to address boundary shares. That is, to treat the boundary share fixed effects $\hat{\delta}_{jh}$'s as censored data rather than outliers. We use an IV Tobit to jointly address censoring and endogeneity. The benefits of this approach over the IVQR are that: (a) as shown below, we argue censoring better describes the data-generating process (DGP) leading to 0% or 100% shares than treating them as outliers, (b) the IV Tobit is older, more well-studied and more widely applied than IVQR (including in software packages, e.g. being built into Stata rather than the user-written packages for IVQR), (c) quantile regression

[9] The IV quantile treatment effects model of Chernozhukov and Hansen was not widely known at the time of the Timmins and Murdock (2007) paper, which uses a rarely employed GMM estimator for an IV quantile regression. Chernozhukov and Hansen (2005; 2006) discuss the drawbacks of GMM relative to their less restrictive model, which is why we employ the latter here.

coefficients, in determining the conditional quantiles (in our case, median) of the dependent variables, are not the same as those in (4), which are the parameters of interest in estimation and are structurally linked to first-stage maximum-likelihood estimation in (5), and finally (d) if the IV Tobit correctly characterizes the DGP (which we test below), then it is generally understood to be more efficient than the IVQR for estimating the parameters of interest.

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. 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 $\hat{\delta}_{jh}$.[10] As compared to the other second-stage IV methods we use, the IV Tobit adds these censoring assumptions, and an assumption that the error

[10] Since this uses less information than with variable bounds, this estimator is still consistent but less efficient than IV Tobit with the highest or lowest known variable bounds.

terms ξ_{jh} in (4) are normally distributed and homoscedastic. 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). 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). Rejection in this test implies a misspecified model, whereas we retrieve a p-value = 0.35.[11]

Another econometric challenge for estimating the RUM specified in (3) and (4) is the potential for price endogeneity. While not the focus of our paper, prices are obviously important in seed demand. Price endogeneity may arise if, for example, within-area market power permits seed sellers to increase their prices to capture rent. This concern is somewhat alleviated because the logic of RUMs implies only between-variety differences $(p_{jh} - p_{kh})$ in prices affect choices in these models. So, for example, if all the p_{jh}'s within area h were marked up by an area-level constant ζ_h, this would not alter the estimated effect of p_{jh} on farmers' seed choices when included in the RUM: Any endogenous markups to price would have to differ by variety to contaminate the RUM with price endogeneity. While this somewhat alleviates the concern, we acknowledge that endogenous premiums for the GM varieties remain possible (Shi, Chavas and Stiegert 2010). We therefore further analyze whether there is a relationship between p_{jh} and measures of area-level market size, which have been shown to be proxies for market power (Campbell and Hopenhayn 2005; Melitz and Ottaviano 2008). The sampling methodology for

[11] 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. The conditional moments test of Pagan and Vella (1989) specifies the null hypothesis $\mathbb{E}[\epsilon_{jh}\boldsymbol{z}_{jh}] = \boldsymbol{0}$ 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.

our survey data provides a convenient measure of market size: the number of sampled corn growers in each village-year, which by design was proportional to the number of corn growers in each village's records. Table A1 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 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.

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:[12]

$$U_{jih} = \delta_{jh} + \boldsymbol{\beta}'\boldsymbol{x}_{ji} + \Delta_{ji} + \epsilon_{jih} \tag{9}$$

with the assumption that $\left(\Delta_{Bt,i}, \Delta_{Stacked,i}\right)$ are jointly i.i.d. $\mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$ 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 $\mathbf{\Sigma}$ of the random effects is to be estimated in addition to the coefficients in (9). This model relaxes the IIA assumption by allowing for

[12] 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.

nonzero off-diagonal elements of $\mathbf{\Sigma}$. Further analysis (table A2) shows that imposing the restriction that $\text{corr}(\Delta_{Bt,i}, \Delta_{Stacked,i}) = 1$ 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 4) assumes a common random effect from either of the GM varieties, with $\Delta_{GM,i} \coloneqq \Delta_{Bt,i} = \Delta_{Stacked,i}$, reducing $\mathbf{\Sigma}$ to a single component, s_{GM}.

The last specification decision we discuss addresses FIML estimation of the pest infestation probit regression in (7). For this model we must select excludable instruments predicting use of the Bt varieties (c_{ih} in eq. 7), but do not directly predicting 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.

6 Results

Table 4 shows the first-stage conditional and mixed logit models, with and without area-level fixed effects. For the purposes of this paper, 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 and mixed logit regressions without area-level fixed effects (first and third 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). Moreover, the effect of seed supplier distance on purchase of the stacked-trait GM variety is statistically significant across three of the four specifications and always has the intuitive sign (greater distance from the seed source leads to a lower likelihood of purchasing the most advanced variety).

The farm's distance to the nearest road also appears to significantly explain demand for the single-trait Bt variety in three of the four specifications. 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 and weeding activities (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 corn 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.

Comparing the conditional and mixed logit models, we see 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 (third column of table 4) yields a statistically significant estimate of σ_{GM}, suggesting the importance of unobserved preference heterogeneity, this additional explanatory power dissipates when area-level fixed effects are included (last column of table 4). An LR test between the mixed and conditional logit models with area-level fixed effects 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.

Concluding our discussion of table 4, we note that in those specifications including seed price its coefficient is of the expected sign and always significant, though only at the 10% level in the baseline conditional logit model. The increased explanatory power attributed to seed price in the mixed logit regression (third column) compared to the conditional logit suggests the role of prices in seed choices is related to unobserved preference heterogeneity. (Recall that seed price is omitted along with all other variety-specific constants from all first-stage specifications with area-level fixed effects, because regressors not varying below the area-level are reserved for second-stage estimation.)

The second-stage regression estimates in table 5 exhibit intuitive patterns and appear to confirm our bioeconomic hypothesis. 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 (cokumn 1) with the IV models (cols. 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 this table.) The other coefficients in these regressions behave as expected in the context of the application: Seed price has a consistently negative marginal utility across all specifications, and is statistically significant in all regressions. The fixed effect of the stacked trait variety is consistently larger than the single-trait variety, which is in turn always greater than zero (with the hybrid variety being reference alternative). Our preferred specification, the IV Tobit in column 5 that allows for endeogeneity 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 strong, 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-stat. = 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 is the importance of accounting for the area-level feedback when estimating the marginal effects of other factors such as prices. For example consider how a marginal decrease in the price of all varieties with Bt traits affects their 'long-run' market shares, based on the estimated RUM with endogenous feedbacks. 'Long-run' in this context means that market shares equilibrate to the endogenous feedbacks estimated here. The immediate direct effect of the price decrease would be to shift market share to the Bt varieties (due to the negative estimated price coefficient in tables 4-5). However, the endogenous sorting model implies that an immediate increase in their market share would be attenuated in equilibrium by the estimated negative (allegedly pest-suppressing) areawide feedback. The magnitude of this attenuation, and the long-run effect of a marginal price change, can be computed by recognizing that the endogenous sorting model estimated implies that the areawide share of Bt seed $\hat{C}(\boldsymbol{X})$ predicted by that area's characteristics $\boldsymbol{X}$ (including seed prices) is an implicit function satisfying $\hat{C}(\boldsymbol{X}) = F\left[\boldsymbol{X}, \hat{C}(\boldsymbol{X})\right]$, where $F(\cdot)$ is defined by the fixed effects conditional logit RUM in (3) and (4); the Appendix explains further. By the Implicit Function Theorem, the gradient of $\hat{C}(\boldsymbol{X})$ is $\hat{C}_{\boldsymbol{X}} = F_{\boldsymbol{X}}(1 - F_c)^{-1}$. A negative coefficient on area-wide Bt shares, $\alpha < 0$, implies $F_C < 0$, as shown in the Appendix, so that the factor $(1 - F_c)^{-1} < 1$ attenuates the magnitudes of the partial derivatives $F_{\boldsymbol{X}}$ in computing $\hat{C}_{\boldsymbol{X}}$. When we apply this formula to compute average price elasticities of demand for the Bt varieties across areas, we find an price elasticity of -1.77 when ignoring the areawide feedback and a long-run elasticity of -0.58 when accounting for areawide feedbacks: the endogenous sorting model, in the IV Tobit specification, reduces the long-run price elasticity of demand for the Bt varieties by 67% compared to the naïve OLS model.

The support the IV models provide for a significant, negative feedback effect from areawide Bt deployment also leads to the question of whether this feedback is in fact bioeconomic; i.e. does it it arise from pest suppression spillovers as hypothesized above? Table 6 addresses this question using the farmers' expectations about ACB infestations. Across all estimated specifications of the FIML model described in section 3.2, we find results highly consistent with our bioeconomic hypothesis, with greater areawide Bt deployment strongly associated with significantly reduced perceived likelihood of infestation. Table 6 reports marginal effects, so that for example a 10% increase in areawide Bt deployment is associated with a minimum 5.6% reduction (first column of table 6) in the likelihood that the farmer indicates expecting ACB infestation.

This marginal effect is robust across specifications, and in fact increases as we account for additional potential sources of bias (moving from left to right in the table), 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 of the type described in 3.2. 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.

7 Discussion

Bioeconomic feedbacks associated with pest control have important implications for agricultural systems. In addition to negative environmental externalities associated with chemical pesticides and the open-access resource issues associated with pesticide resistance, we draw attention to the positive externalities associated with areawide pest suppression spillovers.[13]

[13] On the topic of resistance, it deserves mentioning that one advantage of our data is that it covers a period of time where Bt adoption was widespread, but before any resistance to ACB in the Philippines had been documented.

While previous entomological research has shown these spillovers to be biologically significant, our econometric analysis addresses how these spillovers feed back into farmers' pest control decisions.

This research raises a number of methodological and policy implications and questions for future research. Evidence from prior research and this paper strongly suggest that pest suppression spillovers from Bt crop adoption are significant (as argued by Hutchison et al.) and that these spillovers are likely perceived by farmers (as we find here). In the presence of such spillovers, then farmers who choose not to plant Bt crops initially are more likely to continue to do so *ceteris paribus*, 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," for example avoiding paying the extra technology fee associated with Bt corn rootworm traits, due to low perceived risks from that pest (WSJ 2016).

In the context of areawide pest suppression, economic theory suggests a role for corrective incentives. Efficiency could be improved in principle via a Pigovian subsidy for Bt seed, although such an incentive may also need to account for other possible environmental and bioeconomic externalities, e.g. pest resistance (Ambec and Desquilbet 2012; Brown 2018). That is, an integrated policy should account for both the positive and negative externalities associated with different pest control practices (Lefebvre, Langrell and Gomez-y-Paloma 2015).

An integrated view of these feedbacks is particularly relevant when we compare the implications of our findings – that farmers not using Bt crops are free-riding on those that are using them – with the fact that Bt crops are widely adopted in a variety of contexts. This is true in our data by 2011, in which 5 of the 11 villages exhibited 100% adoption of the stacked trait variety among sampled farmers. And it is also true in the US, where over 84% of corn acreage has been planted to Bt varieties since 2014, with the vast majority (over 95%) of this Bt corn being stacked with HT traits (NASS 2018). This pervasive combination of Bt and HT traits, as well as evidence that seed companies have tended to bundle these traits with their higher yielding conventional germplasm (Shi et al. 2013), complicates arguments of farmers simply free-riding on their peers' Bt deployment. However, it is still possible – as we find in this study – that at the margin farmers face a diminished incentive to plant the Bt trait alone in the presence of significant areawide pest suppression. In the US, for example, the share of corn acreage planted to single trait Bt has monotonically decreased from 27% in 2004 to 2% in 2018 (NASS 2018). Our results (if they were shown to also apply in the US context) could provide one among a number of possible reasons for this secular decrease in use of single-trait Bt varieties. A broader lesson is simply that complex feedbacks, bioeconomic and otherwise, can drive trends in crop choice.

Our suggestive evidence of a pest suppression feedback effect on incentives to use Bt crops warrants more detailed follow-up research in other contexts and using additional types of data. To the extent that we identify a negative feedback between areawide deployment of Bt and individual farmer incentives, we can only interpret it as a net effect. For example, in addition to bioeconomic feedbacks, behavioral peer effects may inform farmers' beliefs about the utility of the technology (Aldana et al. 2012), which could generate positive feedbacks from Bt use (see references in the Introduction). As such, the net negative feedback we find in our analysis may reflect an even larger negative bioeconomic feedback counterbalanced by a positive feedback from peer effects. Nevertheless, our finding that areawide Bt deployment led to reductions in perceived ACB infestation risk, coupled with the fact that transgenic corn was widely available and adopted in the years covered by the data, limit the likelihood that peer effects were a significant source of crop choice feedbacks. Future research combining entomological pest density data with farmer pest control decisions could better disentangle bioeconomic and behavioral feedbacks. Our research suggests this would be a worthwhile effort.

Other agglomeration-inducing endogenous feedbacks may arise in the context of GM corn due to herbicide drift. Recent studies have reported significant damage to US soybean and cotton crops from the drift of the herbicide dicamba. This drift is caused by farmers planting dicamba-resistant varieties and then (illegally) spraying their crops with the herbicide, which then drifts onto neighboring fields planted with non-resistant crops (Bennett 2016). Viewed in the light of the present study, this dynamic would appear to increase growers' demand for dicamba-resistant varieties even if they do not intend to spray dicamba. In the context of our present study with the 'stacked' corn variety including glyphosate resistance and the Bt trait, we do not attempt to identify these potential agglomeration feedbacks, because of somewhat diminished concern about glyphosate drift compared to dicamba (Jordan et al. 2009; Hightower 2017), in particular in the Philippine corn-farming context where farmers generally use knapsack sprayers applying herbicide close to their plants. However, the dicamba drift problem in US cotton and soybeans could provide an important future application of the approach developed here for identifying endogenous feedbacks in crop adoption.

Another implication of this research relates to econometric estimates of yield, profit and income effects of Bt crops. Much of the literature on this topic utilizes observational data, often observing a panel of individual farmers or small spatial units over a number of years (Fernandez-Cornejo and Wechsler 2012; Kathage and Qaim 2012; Mutuc and Rejesus 2012; Xu et al. 2013; Sanglestsawai et al. 2014; Qiao 2015). While much of this econometric work addresses the potential endogeneity of Bt adoption owing to selection, our research suggests there may be another source of bias arising from the fact that farmer-level adoption is likely correlated with areawide adoption and hence possibly associated with pest suppression spillovers and resulting yield gains. This suggests that econometric studies using farmer-level data may overestimate the direct effect of Bt adoption on key outcomes such as yield and profit, even when controlling for selection. Such areawide feedbacks may not only generate a potential source of bias, and may for example play a role in seeming inconsistencies between micro-level and aggregate analyses of the yield impacts of Bt crops (NASEM 2016; Lusk, Tack and Hendricks 2016). At the very least because the nature of such bioeconomic spillovers is inherently dynamic, the present analysis provides motivation for yield regressions to include flexible fixed effects *interactions* between geographic areas and temporal units or trends (the main effects for which are standard in such yield regressions), at least if one aims to isolate the own-farm yield effects of transgenic crop deployment. Of course, such flexible fixed effects specifications could place extreme demands on the datasets typically used for these yield regressions.

Recognizing these areawide bioeconomic feedbacks suggests alternative ways of eliminating bias from these regressions: Estimate the two-stage endogenous sorting model described above to generate predicted farmer-level adoption probabilities, controlling for selection *and* areawide adoption feedbacks, and then use these predicted probabilities to estimate the effects of adoption on key outcomes such as yield and profit. Considering that controlling for selection alone makes significant demands on the data for achieving sufficient statistical power, we reserve such an exercise for future work with richer data.

Appendix

[Tables A1- A2]

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:

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

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:

$$\frac{d\hat{C}_h}{dp_{Hh}} = \frac{\frac{\partial F_h}{\partial p_{Hh}}}{\left(1-\frac{\partial F_h}{\partial C_h}\right)} = \frac{-n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial p_{Hh}}}{\left(1+n_h^{-1}\sum_{i\in h}\frac{\partial P_{Hih}}{\partial C_h}\right)} \qquad \text{(A1)}$$

Because p_{Hh} is the logarithm of price throughout the manuscript, (A1) 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 (A1) 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 A3 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 (A1) 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 A3 here]

Tables

Table 1: Corn 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 corn 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%

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

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 conditional and mixed logit estimates.

	Conditional logit		*Mixed logit*	
Log(seed price)	-1.071*	[in fixed effect]	-1.910**	[in fixed effect]
	(0.564)		(0.837)	
Bt single-trait ×				
Constant	0.233	[in fixed effect]	0.791	[in fixed effect]
	(0.385)		(0.603)	
Distance to seed source	0.0288***	0.0149	0.0352*	0.0159
	(0.0105)	(0.00967)	(0.0186)	(0.0136)
Rolling terrain	0.865**	0.139	0.875*	0.158
	(0.342)	(0.320)	(0.469)	(0.367)
Hilly/mountainous terrain	-0.561	-1.005***	-0.650	-1.056***
	(0.344)	(0.352)	(0.493)	(0.390)
Distance to nearest road	0.244	0.362**	0.290	0.377***
	(0.165)	(0.153)	(0.177)	(0.139)
Years farming corn	0.00197	0.00125	0.00331	0.00186
	(0.0132)	(0.00781)	(0.0182)	(0.00849)
Stacked variety ×			0.0352*	0.0159
Constant	2.463***	[in fixed effect]	3.404***	[in fixed effect]
	(0.530)		(0.765)	
Distance to seed source	-0.0490**	-0.0714*	-0.0426	-0.0707*
	(0.0217)	(0.0409)	(0.0291)	(0.0379)
Rolling terrain	2.228***	1.245*	2.312***	1.345
	(0.733)	(0.730)	(0.774)	(0.936)
Hilly/mountainous terrain	-0.360	-0.875	-0.120	-0.869
	(0.446)	(0.640)	(0.523)	(0.608)
Distance to nearest road	0.102	0.111	0.0664	0.122
	(0.246)	(0.242)	(0.203)	(0.206)
Years farming corn	0.0289	0.0149	0.0339	0.0171
	(0.0215)	(0.0172)	(0.0225)	(0.0167)
Random parameters				
s_{GM}[a]			1.767***	0.658
			(0.357)	(0.442)
Area fixed effects[b]	No	Yes	No	Yes
Choice occasions	515	515	515	515
Farmers	261	261	261	261
Deg. Freedom	13	10	14	11
Log-likelihood	-313.6	-220.9	-304.8	-220.2
Wald-χ^2	196.66***	41.11***	126.76***	23.69***
Pseudo-R^2	0.321	0.0575	0.341	0.0596

Table 4 notes: Robust standard errors clustered at the grower level and in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. [a] s_{GM} is the estimated standard deviation in a mixed logit model for a random parameter associated with both the GM seed varaieties: single trait B or stacked trait; see section 3.2. [b]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 regression estimates.

	OLS		2SLS[a]	IVQR[a,b]	IV Tobit[a,b]
	(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 inappropriateness of jackknifed standard errors for quantile regression (Shao and Wu 1989) and the 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); previous econometric analysis using these methods follows this approach and has shown the first-stage measurement error tends to have a small effect on standard errors (Berry, Linton and Pakes 2004; Timmins and Murdock 2007; Hicks et al. 2012). [c] Pseudo-R^2 reported based on joint null and MLE log-likelihoods.

Table 6. Marginal effects on probability of farmer expecting corn borer infestation in coming season.

	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 corn	0.00331**	0.00323**	0.00185	0.00185	0.00171
	(0.00150)	(0.00148)	(0.00142)	(0.00180)	(0.00171)
Cross-eq. residual correlation (τ)				0.540	0.795*
				(0.372)	(0.208)
Village-level fixed effects	No	No	Yes	Yes	Yes
Excluded instruments [a]				All	Only GM seed premium
F-stat 1st stage instruments				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 corn. Instruments include village-level mean GM seed premium, farm distance to seed source and distance to nearest road.

Table A1. Ordinary least squares regression of seed prices on village-level sample size (n_v).

Dependent variable: 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, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. First-stage seed choice, mixed logit specification tests

	(1)	(2)
Log(seed price)	-1.214	-1.910**
	(0.850)	(0.837)
Bt single-trait ×		
Constant	0.488	0.791
	(0.557)	(0.603)
Distance to seed source	0.0321*	0.0352*
	(0.0169)	(0.0186)
Rolling terrain	0.730*	0.875*
	(0.418)	(0.469)
Hilly/mountainous terrain	-0.627	-0.650
	(0.440)	(0.493)
Distance to nearest road	0.261*	0.290
	(0.155)	(0.177)
Years farming corn	0.00447	0.00331
	(0.0156)	(0.0182)
Stacked variety ×		
Constant	3.189***	3.404***
	(0.740)	(0.765)
Distance to seed source	-0.0576	-0.0426
	(0.0376)	(0.0291)
Rolling terrain	2.482***	2.312***
	(0.923)	(0.774)
Hilly/mountainous terrain	-0.0355	-0.120
	(0.596)	(0.523)
Distance to nearest road	0.0256	0.0664
	(0.232)	(0.203)
Years farming corn	0.0398	0.0339
	(0.0262)	(0.0225)
Random parameters		
s_{GM}		1.767***
		(0.357)
s_{Bt}	1.260***	
	(0.454)	
s_{Stacked}	2.182***	
	(0.650)	
$s_{\text{Bt,Stacked}}$	2.750***	
	(1.040)	
Area fixed effects[1]	No	No
Choice occasions	515	515
Farmers	261	261
Deg. Freedom	16	14
Log-likelihood	-303.7	-304.8
Pseudo-R^2	0.343	0.341

Table A2 notes: Robust standard errors clustered at the grower level and in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. [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. Pseudo-R^2 calculations in fixed-effect models calculated relative to a null conditional logit model with only area-level fixed effects.

Table A3. 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 A3 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.

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