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

Zachary S. Brown*[1] Lawson Connor[1] Rod Rejesus[1] Jose Yorobe[2]

July 2016

Abstract

Farmer control of agricultural pests raises the possibility of bio-economic 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. This negative feedback is analogous to a congestion externality. While economists have written theoretically about this feedback or modeled it in simulations of bio-invasions, they rarely measure it econometrically. Here we introduce an econometric methodology developed for endogenous sorting models in the environmental and urban economics literatures to study bio-economic feedbacks in pest control. We apply this framework to study area-level use of Bt and potential feedbacks from individuals' decisions to use of transgenic Bt corn, using a panel dataset from the Philippines. In a simple conceptual model, we confirm that a bio-economic feedback through pest suppression should manifest as a congestion effect. Identification in the econometric model is achieved by combining fixed effects conditional logit estimation of crop choice with instrumental variables methods. We find some evidence for a negative feedback associated with the use of transgenic corn in the Philippines, though this feedback appears to be mostly outweighed by other beneficial traits of Bt corn (especially when combined with herbicide tolerance traits). Consistent with this bio-economic view, weighting regression observations by farm size greatly strengthens the evidence for a pest suppression feedback in crop variety choice.

Keywords: Bioeconomic spillovers, areawide pest control, endogenous sorting, agricultural biotechnology

JEL codes: C25, C26, Q12, Q16, Q51, Q57, O13

Author affiliations:

* Corresponding author: zack_brown@ncsu.edu

1. North Carolina State University, Raleigh, NC, USA

2. University of the Philippines – Los Banos

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 2005; 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 engineered 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' choice about use of different biotechnology responds to bio-economic spillovers from pest control.[1] This is in spite of the demonstrable economic significance of bio-economic spillovers. Hutchison et al. (2010) study pesticidal transgenic corn adoption in the Mistwestern US, and investigate the area-wide effects of the technology on European corn borer (ECB), historically a major corn pest in this region. They show that widespread adoption of the

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

transgenic variety caused area-wide reductions in ECB densities, providing an estimated $4.3 billion worth of pest suppression benefits to *non*-adopters of the transgenic varieties: approximately 60% of the overall pest reduction benefits provided by these varieties. A natural conjecture – one that Hutchison et al. do not analyze – is that individual incentives to adopt the transgenic varieties decrease with greater area-wide 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 a pesticidal crop variety. 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 bio-economic pest suppression feedbacks should manifest as a congestion-like effect.

The endogeneity created by these feedbacks requires an econometric identification strategy. Currently, the dominant method is an instrumental variables (IV) technique developed by Bayer and Timmins (2007). This technique utilizes area-level variation in exogenous characteristics and choice sets to instrument for area-wide, variety-specific adoption shares, and then uses these instrumented shares as inputs to a random utility model (RUM) of individual choice of alternatives (in our application, seed varieties). Formally, the method consists of two stages. The first stage consists of estimating a discrete choice model with area-alternative fixed effects by, for example computed 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. This variation along choice, space and time dimensions facilitate identification of endogenous spillovers. The estimation results show evidence of a congestion effect associated with transgene corn adoption in the Philippines.[2] Our results suggest that the bio-economic spillovers (congestion) outweigh the benefits of further adoption of Bt in equilibrium in this context but benefits to adoption of the stacked trait outweigh the bio-economic congestion spillover associated with large scale Bt adoption.

The implications of these results, taken together, are that it is important to account for spillover effects in modeling crop adoption decisions, which may have area-wide effects when aggregated. Excluding – or naively including – spillovers may lead to biased estimation of the economic value of the transgenic varieties when using choice data. The next section presents both a conceptual model of the spillover in the context of pest control via transgenic crop adoption and a description of the econometric model and estimation method. We then provide a description of the dataset and empirical context, before discussing some econometric complications posed by the data and presenting estimation results. We then interpret these results and draw lessons for future research on this topic.

[2] We lack explicit data on ACB densities and so the power of estimation of the effect is somewhat reduced.

2 Literature review

There have been many studies that have attempted to estimate the benefits of adopting pesticidal crops for farmers and the 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) bio-economic 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 area-wide by application of these pesticides.

Hutchison et. al. (2010) indicate that similar area-wide spillovers exist with Bt adoption as well. 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. Hutchinson et al show benefits that of this reduction in pest numbers are experienced to a greater extent by non-adopters who avoid paying the cost of pest management (since transgenic seeds are more expensive than non-transgenic ones). This reduces incentives to further adopt transgenic Bt corn as a means pest management, creating the potential for endogenous sorting in seed type choice.

Estimation of discrete choice models with endogenous sorting is a major research area in the hedonic valuation literature within environmental and urban economics. Schelling (1969; 1971) provides 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. This theoretical framework is able to capture *congestion* phenomena, in which the relative utility conveyed by a particular alternative (housing location, recreational site, etc.) decreases as others adopt that alternative, and *agglomeration,* in which the utility of an alternative is enhanced as others adopt it. Brito et al. (1991) are the first to show how Schelling's theoretical framework can be applied to bio-economic 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. 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 (we discuss their method in detail in a subsequent section). However, through Monte Carlo Simulation analysis they show that the method performs well and is robust to distributional and functional form assumptions, as long as sufficient variation in alternatives and exogenous factors exist. Many applications of their IV method in urban and environmental economics have estimated, for example, the value of opens 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 bio-economic spillovers associated with renewable resource depletion. 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 bio-economic 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 bio-economic spillover) and in turn determine individual grower choices about whether to adopt transgenic varieties. We demonstrate how the bio-economic spillover could be expected to manifest as a congestion effect, which can cause lower than expected levels of adoption of the single trait Bt crop. We then translate this conceptual model into an econometric approach, and describe the estimation procedure.

3.1 Conceptual model

We construct a stylized model of pesticidal crop adoption to show that bio-economic pest suppression spillovers should result in a negative feedback on adoption. Consider a farmer facing the *ex ante* binary choice of whether to plant one of two varieties of a crop at the beginning of a growing season. The farmer may select a conventional variety fully susceptible to pest damage or a pesticidal variety that protects the plant from damage and also kills the major insect pest in the region (as is the case with Bt corn in the Philippines). 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, we focus in our conceptual model only on uncertainty with respect to pest densities in the upcoming season. Let $\pi_H(d)$ be the *ex post* profit 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 area-wide Bt use 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 in the upcoming season conditional on area-wide adoption 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 area-wide 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* profit differential $\rho(C) \coloneqq \pi_{Bt} - w - \Pi_H(C)$.

A generic way to model a pest suppression effect of area-wide 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.[3] 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, easily

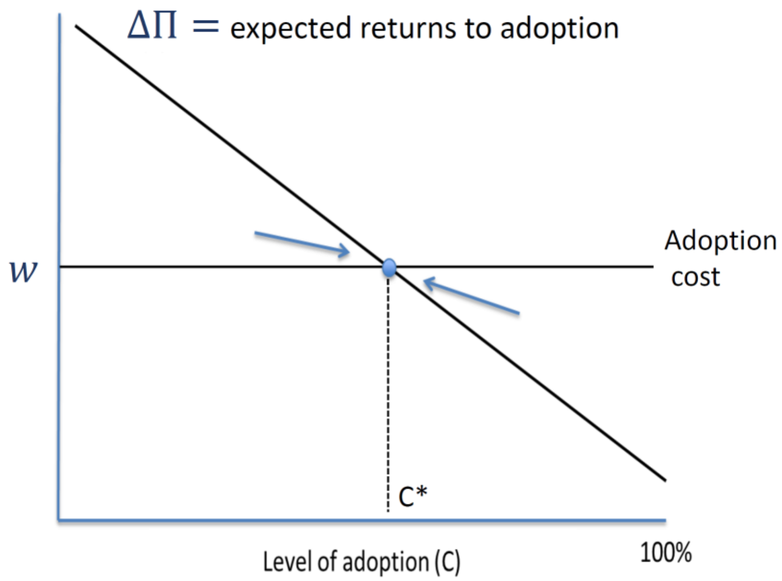
[3] Alternatively, a pest control method could feasibly result in repelling – rather than suppressing – pests from areas where the method is used to areas where the method was is not used. In this case CDFs conditional on *lower* use could first-order stochastically dominate those with higher adoption, 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, Bt crops kill pest larvae before they can realistically spread to neighboring farms, and so the technology is definitively pest suppressing, as previously discussed, and not repelling at an area-wide scale.

shown implication of first-order stochastic dominance). Consequently, the expected profit gain from the Bt variety relative to the hybrid variety is decreasing in area-wide adoption, i.e. $\partial\rho/\partial C < 0$.

This provides a basic, intuitive model of a negative, pest suppression feedback from pesticidal crop adoption. Equilibrium properties are straight forward to see, 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 area-wide adoption is below equilibrium, and disincentive to adopt if area-wide 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 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.

Note that this model is not one of learning. It presumes the grower knows his conditional expected profits $\Pi_{Bt}(C)$ and $\Pi_H(C)$, Bt price premium w, as well as the conditional pest damage CDF $F(d|C)$. They do not, for example, learn and update their beliefs about these factors through based on past experience, as Aldana et al. (2011) argue, or through social learning in which farmers update beliefs by observing their peers. We argue that learning dynamics are less relevant in our data for reasons described below. We discuss at the end of the paper how learning dynamics could affect the results.

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



3.2 Econometric model

To empirically evaluate the presence of agglomeration or congestion effects, we apply an IV method developed by Bayer and Timmins (2007) to estimate discrete choice econometric RUMs with endogenous sorting between crop varieties. In the context of our application, we specify the *ex ante* utility to the farmer of crop variety j for grower i in area h as $U_{jih} = \beta x_{ji} + \alpha C_{jh} - \eta p_{jh} + \xi_{jh} + \epsilon_{jih}$, which can be expressed by consolidating all area-level terms into the area-level utility effect δ_{jh}:

$$U_{jih} = \beta x_{ji} + \delta_{jh} + \epsilon_{jih} \quad (3)$$

with the associated decomposition of area-level effects:

$$\delta_{jh} = \bar{\delta}_j + \alpha C_{jh} - \eta p_{jh} + \xi_{jh} \quad (4)$$

The vector x_i contains grower-specific characteristics, p_{jh} is the price of variety j in area h, and C_{jh} is the fraction of growers in area h selecting variety j. The Greek letters are taste parameters (or vectors of parameters) to be estimated, except for ξ_{jh} and ϵ_{jih}, which are unobservable area-level and individual-level random utility components. Given our conceptual model, the parameter of particular interest is the spillover effect, α: Negative values for this parameter imply a negative, congestion-like feedback, and positive values imply a positive, agglomeration-like feedback.[4] Here, *ex ante* utility can be interpreted as implicitly containing the expected profit from selecting seed type 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).

Assuming that the random utility component ϵ_{jih} in (4) is iid extreme value, we obtain the conditional logit model for the probability p_{jih} of grower i selecting variety j in area h:

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

The standard approach to estimating this model is via a two-stage approach. In the first stage, estimates $\hat{\beta}$ and $\hat{\delta}_{jh}$ are obtained from maximum-likelihood estimation combined with a contraction mapping algorithm introduced by Berry et al. (1995). This method (and newly developed alternatives: Dubé, Fox and Su 2012) ensures that the predicted market shares $\hat{C}_{jh} \equiv \frac{1}{n_h}\sum_{i\in h} p_{jih}(\hat{\beta},\hat{\delta})$ equal the observed market shares C_{jh} (where n_h is the area-level sample size).[5] In the second stage, the estimated $\hat{\delta}_{jh}$ are used as dependent variables in a linear regression on

[4] It is possible for there to exist nonlinear spillover effects, as has been shown in other contexts (Hicks et al. 2012). However, our empirical application does not permit enough statistical power to estimate such nonlinearities, or to separately identify the sources of congestion versus possible sources of agglomeration.

[5] Note that identified estimation of the δ_{jh}'s requires an arbitrary normalization, for example, that the mean fixed effect for some reference variety is 0, which is normalization we adopt here, with the conventional hybrid defined as the reference variety.

observable variety-specific factors varying at the area level, using the decomposition in (5) and treating the unobserved area-level component ξ_{jh} as a regression error.

In our application (and in the endogenous sorting literature generally), area-level explanatory variables in the second stage include the area-level, variety-specific share C_{jh}. This creates an obvious endogeneity problem, since the $\hat{\delta}_{jh}$'s are themselves estimated in the first stage to satisfy $\hat{C}_{jh} = C_{jh}$. Econometrically, this endogeneity problem can be stated as $\text{Cov}(C_{jh}, \xi_{jh}) \neq 0$. As Timmins and Murdock (2007) point out, the tendency is for $\text{Cov}(C_{jh}, \xi_{jh}) > 0$, meaning that adoption may look as if it is highly agglomerative when in fact unobserved area-level factors are giving rise to correlated adoption. In our case, such unobserved factors may include the ecological suitability for Asian Corn Borer (ACB), soil productivity, farmer capital stock, experience and ability, as well as differences in preexisting social norms between areas. The other area-level explanatory variable in (5), the seed prices p_{jh}, are assumed here to be exogenous based on our empirical context (described below) although these also may be addressed by the IV approach that follows.

The IV approach proposed by Bayer and Timmins (2007) is to use between-area differences in exogenous characteristics (including differences in available varieties comprising the choice sets) to form instruments. They demonstrate the validity of this estimator using Monte Carlo analysis. In the context of the model presented in (4), this IV is:

$$\tilde{C}_{jh} = \frac{1}{n_h} \sum_{i \in h} \frac{\exp\{\tilde{\beta} x_{ji} - \tilde{\eta} p_{jh}\}}{\sum_{k \in h} \exp\{\tilde{\beta} x_{ki} - \tilde{\eta} p_{kh}\}} \tag{6}$$

where $\tilde{\beta}$ and $\tilde{\eta}$ are initial 'guesses' of their respective parameters. Bayer and Timmins postulate that any initial guess $\tilde{\beta}$ and $\tilde{\eta}$ leads to 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 $\hat{\delta}_{jh}$

only on p_{jh} to obtain an initial guess of $\tilde{\eta}$ (Timmins and Murdock 2007; Hicks et al. 2012). We use this approach in our application.

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 ACB (Morallo-Rejesus, Belen G. Punzalan 2002). Over approximately the past decade, ACB infestation 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 (i.e., China). Gerpacio et al. also report that corn farmers in major producing regions only apply insecticides when infestation is high.

Given ACB's dominance as the major insect pest for corn in the country, the agricultural sector was naturally interested in transgenic Bt corn varieties as a means of control. In December 2002, after extensive field trials, the Philippine Department of Agriculture (DA) provided regulations for the commercial use of GM crops and approved the commercial distribution of Bt corn (specifically Monsanto's YieldgardTM 818 and 838). In the first year of its commercial use, 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 (i.e. subjective perceptions about the technology). The surveys were conducted through face-to-face interviews using pre-tested questionnaires.

The survey was confined to the provinces of Isabela and South Cotabato, both major corn-producing provinces with significant adoption and prior experience with hybrid and transgenic varieties at the time of the survey. This fact is why we do not focus on learning dynamics in our choice model. 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 barangays from four towns were selected from these two sites. The farmers interviewed were randomly chosen from lists of all yellow corn growers in each barangay. In addition, the 2010 sample included farmers planting a new stacked variety introduced into the market four years prior (2006). This new variety possessed a trait which additionally conferred resistance to the herbicide glyphosate (such traits are commercially available as 'Round-Up Ready,' in light of Monsanto's trade-name for glyphosate).

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 692 total observations of farmers remained from the two survey periods. In 2007, 207 of these farmers planted hybrid corn and 221 planted Bt. In the second year, 28 planted hybrid, 21 planted Bt and 215 planted the stacked variety. 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.

To estimate the choice models used in this study, we require subsets of variables that differ over area, individual and variety. According to the method of Bayer and Timmins (*ibid.*), identification requirements for these variables are that they should be exogenous to both individual choices and area-level adoption of transgenic varieties. At the individual level, we include individual growers' distances to the nearest seed supply retail 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, as well as indicators of the farm's terrain. Because these variables only vary by grower – and not by corn variety – we interact these grower-level variables with variety-specific dummy variables before including in the choice model. Justifying hypotheses for this approach would be that grower-level variables differentially determine the net utility of each variety. One such hypothesis for the distance to roads and seed retailer variables – as argued by Sanglestsawai et al. – is that hybrid seed may be easier to access from neighbors are extension, whereas transgenic varieties must mainly be purchased from a retailer.

To obtain variety-specific prices which vary by area, we use an approach similar to Bayer et al. (2009) and Klaiber and Phaneuf (2010), regressing prices farmers paid for seeds on village fixed effects interacted with seed type and a year dummy. We use the coefficients produced in these regressions to predict variety-specific, area-level prices in 2007 and 2011. In econometric estimation, we treat seed prices as exogenous with area-level adoption, based on interviews from local researchers and extension personnel.

4.1 Summary statistics

Table 1 summarizes the adoption shares for the different seed types by village (corresponding to the C_{ji} 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 with regard to the stacked trait variety. Third, five of the 11 villages in 2011 have 100% adoption of the stacked-trait variety for the sampled farmers. This will pose some complications for our proposed econometric approach, discussed below.

Table 2 summarizes the grower-level variables used in this analysis. The average grower in the sample has been farming corn for over two decades with over two thirds of their farms located on flat terrain. For the purposes of this paper, the main point of this table is to show that significant heterogeneity in these variables exists both within and between villages. In this regard we see that between 30% and 60% of the total variation in each of these variables is captured by between-villages differences.

Table 3 summarizes the imputed 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-trait product is 65% of the mean hybrid seed price in 2011. Meanwhile, the estimated time trend for the hybrid variety was an increase between 2007 and 2011 of 48%.

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	*Std. dev.*	*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%

Notes: 1. Standard deviation in village-level means, 2. Defined as the standard deviation of village-level 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.

5 Econometric estimation

In light of the data described above, some complications arise that must be addressed to implement our econometric approach. We first discuss how we address these complications before presenting estimation results.

5.1 Practical considerations in implementing the estimation method

The most significant empirical challenge to implementing our econometric approach with the available 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 estimated $\hat{\delta}_{jh}$'s will converge to negative or positive infinity in these cases (since these estimates bring estimated area-level market shares in line with their empirical counterparts by design). Such outlier cases will bias estimates obtained from the second-stage regression employing these estimated $\hat{\delta}_{jh}$'s as dependent variables in an ordinary least squares regression.

To deal with this problem of adoption shares at the boundary, we adopt the same approach used by Timmins and Murdock (2007). They modify boundary shares by a very small number (e.g. 1e-4), to ensure convergence of the contraction mapping algorithm, albeit to very large magnitude (but finite) values for $\hat{\delta}_{jh}$. To avoid these large-magnitude boundary $\hat{\delta}_{jh}$'s serving as outliers biasing the regression, they then adopt an IV median (quantile) regression in the second-stage in place of a two-stage least squares regression. Timmins and Murdock explain that the use of a quantile regression approach is simply due to these outlier problems, not because they are particularly interested in estimating quantile effects *per se*.

Additionally, estimates of C_{jh} recovered from the model specified thus far represent the proportion of farms in a village planting each variety. However, we expect that the total area of farmland planted with pesticidal corn influences area-wide pest pressure more so than the number of farms planting pesticidal corn. For example, a handful of large farms adopting pesticidal corn could have significant area-wide pest suppression effects and subsequent disincentives for further adoption, even if these large farmers represent only a small share of farmers in the area. As such, we also estimate second-stage regression models in which we calculate adoption shares (raw and instrumented) weighting by farm-area. Because this should be a better measure of any bio-economic spillover, we expect a stronger spillover signal from such a regression.

5.2 Estimation results

We start by presenting results from the first-stage conditional logit model, with and without area-level fixed effects (**Table 4**). In the baseline conditional logit regression, a number of the variables appear to be statistically significant predictors of adoption. As in Sanglestsawai et al., variety-specific prices are statistically significant negative predictors of a given variety, and distance to the grower's nearest seed source is a statistically significant predictor of single-trait and stacked-trait adoption. Years farming corn does not seem to be statistically significant in predicting adoption. Finally, the terrain variables also appear to play a role in predicting adoption, with 'rolling' terrain appearing to be more associated with transgenic adoption (than flat or mountainous terrain).

Comparing the baseline conditional logit specification (first column) to the area-level fixed effects conditional logit (last column) in Table 4, we see that most of the estimated coefficients for the grower-level variables retain their sign, but with generally lower statistical precision on the estimates. (We exclude area-level variables, such as price, from the first-stage fixed effects regression, due to their collinearity with the fixed effects. These are included in the second-stage regression. Also, note that in Tables 4 and 5 the coefficient magnitudes cannot be directly compared between the specifications, due to unidentified scale differences.) The instrument for adoption shares are constructed as described in Section 3.2, following previous researchers. **Figures 1** and **2** show the instrument performs well, in terms of providing significant explanatory power for empirical adoption shares.

Table 5 provides estimates from the second stage regression, with the five different ways ways of handling the spillover effect. All five specifications use a median regression to deal with boundary shares, as described above. In the first column, spillover effects are simply excluded. In columns 2 and 3, spillover effects are included without instrumenting; column 2 uses raw shares whereas column 3 uses area-weighting. Columns 4 and 5 present IV estimates with those in column 4 being the area-weighted shares.

As with previous endogenous sorting models of bio-economic feedbacks, the naïve estimator implies agglomerative feedbacks, where the IV approach implies congestion as hypothesized in a conceptual model in Section 3.1. Moreover, there appears to be more of a statistical signal of a bio-economic spillover when area-weighted adoption shares are used, consistent with an underlying pest suppression feedback. As for other coefficients, the price coefficient is negative in all specifications (though only statistically significant in the area-weighted specification).

There also clearly appears to be a greater preference by farmers for the stacked trait variety relative to the single-trait Bt product, as suggested by the relatively larger coefficient on the stacked trait dummy relative compared to the Bt single trait dummy. For proper accounting, the linear combination of first-stage coefficients β with variety-farmer covariates x_{ji}, referring to eq. (3), should be included in calculations of total mean direct utility $\bar{u}_j$ for each variety, apart from price effects and spillovers. The variety-specific mean utility calculation is $\bar{u}_j \coloneqq \beta\bar{x}_j + \bar{\delta}_j$, where $\bar{x}_j \coloneqq N^{-1} \sum_i \; x_{ji}$ is the mean of the respondent covariates vector (interacted with the variety dummy) and $\bar{\delta}_j$ is the variety-specific constants from the second stage regression (the second and third coefficient rows in Table 5). This calculation implies the stacked trait variety is indeed more valuable than the Bt single trait variety, across all models except in the naïve, area-weighted regression. In our preferred regression (area-weighted IV), the estimated value of the stacked trait variety is 2.9 times the value of the Bt single-trait variety (this relative estimate can be interpreted in utility or monetary terms).

While the raw coefficients on the spillover effects from the second-stage regression do not have meaningful units, we use the seed price coefficient in this regression to monetize the spillover effects, expressing in terms of effects on marginal willingness to pay (MWTP) for seed. The spillover effect of a 10% increase in area-wide adoption of a given variety, in terms of the MWTP for seed of the same variety can be calculated as $\frac{\alpha}{\eta} \times 10\%$, with α and η being the coefficients on adoption share and price respectively (as in eq. 4). **Table 6** shows these estimates. The IV models implies that a 10% increase in area-wide adoption (in terms of fraction of farmers) of the single-trait Bt variety would lead to a decrease of approximately 5% in the MWTP for single-trait Bt seed for the same variety. When adoption is measured instead as a percentage of planted area (weighting adoption by farm size), a 10% increase in the area planted to the single-trait Bt variety would lead to approximately a 14% decrease in MWTP.

Figure 1: Village-level adoption, empirical versus instruments

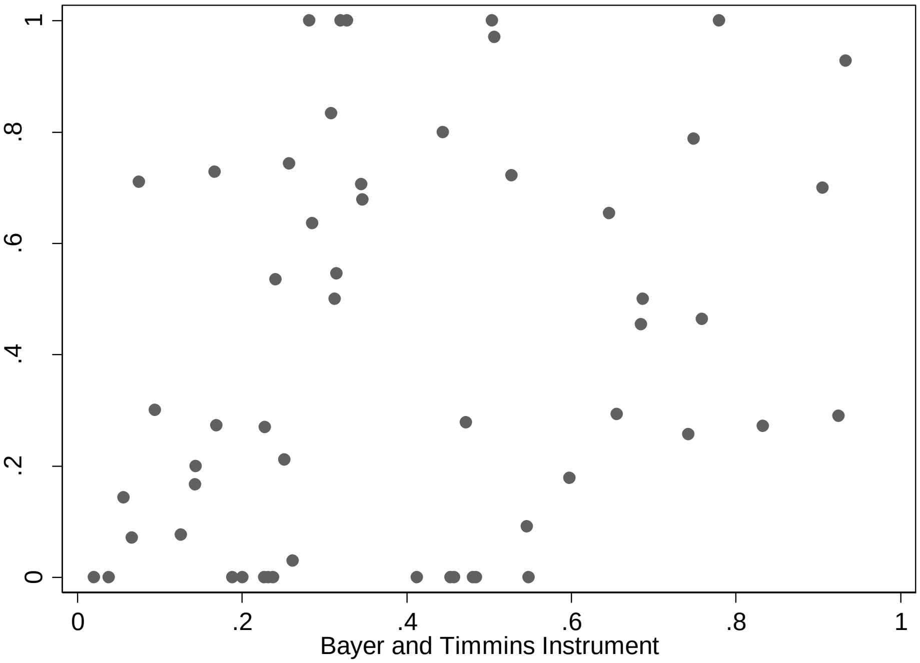


Figure 2: Village-level adoption, empirical vs instrumented area-weighted shares

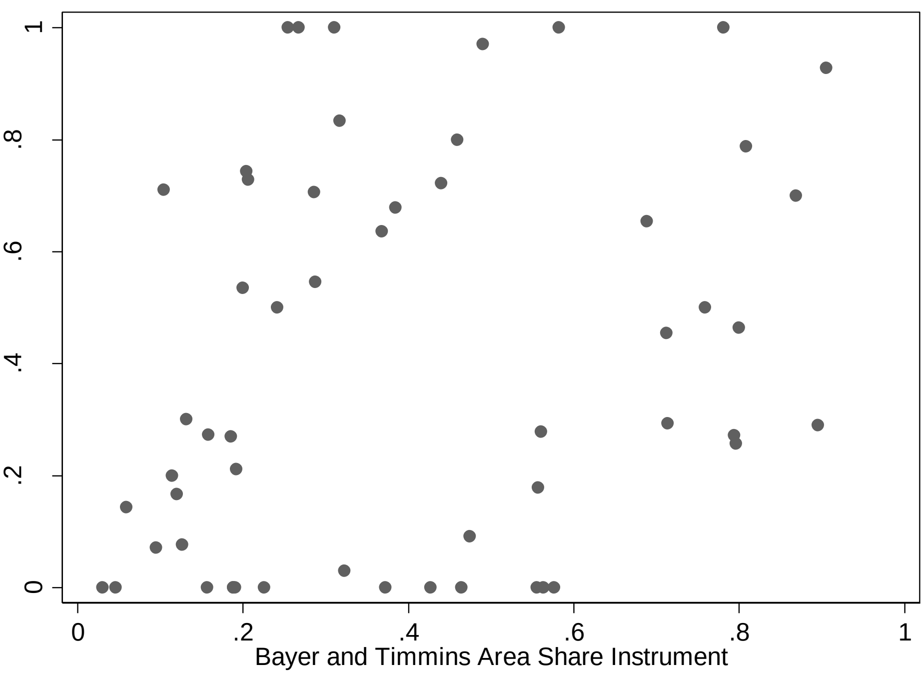


Table 4: First-stage conditional logit estimates

	Conditional logit	*Area-level Fixed effects*[1]
Seed Price (PHP)	-0.00403*	n/a
	(0.00227)	
Bt single-trait ×		
Constant	0.320	n/a
	(0.395)	
Distance to seed source	0.0288***	0.0139
	(0.0105)	(0.00992)
Rolling terrain	0.815**	0.0812
	(0.337)	(0.323)
Hilly or mountainous terrain	-0.658*	-1.126***
	(0.342)	(0.362)
Distance to nearest road	0.288*	0.485**
	(0.171)	(0.218)
Years farming corn	-0.00313	0.00614
	(0.0128)	(0.00775)
Stacked variety ×		
Constant	2.732***	n/a
	(0.646)	
Distance to seed source	-0.0510**	-0.0704*
	(0.0216)	(0.0401)
Rolling terrain	2.132***	1.304*
	(0.723)	(0.708)
Hilly or mountainous terrain	-0.423	-0.895
	(0.435)	(0.635)
Distance to nearest road	0.128	0.235
	(0.249)	(0.317)
Years farming corn	0.0195	0.0262*
	(0.0205)	(0.0155)
Observations (choice tasks)	1,320	1,320
Deg. freedom	13	10
Log-likelihood	-319.9	-228.6
Pseudo-R^2	0.324	0.0698

Notes: Robust standard errors clustered at the grower level and in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1. Area-level fixed effects model calculated using contraction mapping algorithm (Berry et al. 1995). Area level coefficients are not applicable (n/a) of this model as they are collinear with area-level effects.

Table 5: Second-stage median regression estimates

	Median Regression: (no spillover)	*Naïve median regression*		*IV median regression*	
		Raw	*Size-weighted shares*	*Raw*	*Size-weighted shares*
Seed Price	-0.0101	-0.0144	-0.00323	-0.0203	-0.0961**
(PHP)	(0.0159)	(0.0144)	(0.0150)	(0.0178)	(0.0404)
Variety					
Bt single-trait	0.443	1.252	0.277	1.283	17.37***
	(2.876)	(2.459)	(2.607)	(2.808)	(5.952)
Stacked	3.365	2.313	-0.316	7.264*	50.06***
	(4.320)	(4.744)	(5.046)	(4.332)	(9.429)
Adoption share		4.193	3.103	-2.748	-35.69***
		(3.470)	(3.549)	(4.720)	(10.36)
Constant	4.683	3.741	2.228	7.684	29.95**
	(4.139)	(4.172)	(4.281)	(5.796)	(13.54)
Observations	55	55	55	55	55

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We follow the prevailing practice of using standard errors directly reported in this second stage, which is justifiable as long as the number of estimated $\hat{\delta}_{jh}$'s is sufficiently large for asymptotic properties of the estimator to obtain (Berry, Linton and Pakes 2004; Bayer and Timmins 2007).

Table 6. Effect on marginal willingness to pay for seed of 10% increase in same variety area-wide adoption

	Naïve models		*IV models*	
	Raw	*Size-weighted*	*Raw*	*Size-weighted*
PHP per kilo	29.12	96.07	-13.54	-37.14
Percent of mean 2011 Bt seed price	10.63%	35.06%	-4.94%	-13.55%

6 Discussion

Bioeconomic feedbacks associated with pest control have important implications for agricultural systems. Apart from negative environmental externalities associated with chemical pesticides and the open-access resource issues associated with pesticide resistance (Florax, Travisi and Nijkamp 2005; Miranowski and Carlson 1986), we draw attention to another type of positive externality from pest control: the positive externalities associated with area-wide pest suppression spillovers.[6] 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. If area-wide pest suppression spillovers from Bt crop adoption are significant (as argued by Hutchison et al.), then non-adopting farmers' are more likely to remain so *ceteris paribus*. Indeed, recent 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 area-wide pest suppression, economic theory suggests a role for corrective incentives. Farmers engaging in greater pest control efforts (such as paying the extra cost of transgenic pesticidal corn) should be compensated via a Pigovian subsidy, in addition to possibly negative corrective economic incentives associated with environmental externalities or pest resistance (e.g. Pigovian taxes or existing Bt refuge policies, Vacher et al. 2006). That is,

[6] 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.

coherent policy should account for both the positive and negative externalities associated with different pest control practices.

Our suggestive evidence of a congestion effect of transgenic pesticidal corn adoption – consistent with a pest suppression spillover – warrants more detailed follow-up research in other contexts and using additional types of data. To the extent that we identify an adoption spillover, we can really only interpret it in the aggregate. For example, in addition to bioeconomic feedbacks, there may also be behavioral peer effects at play, which would be likely to manifest as agglomeration (see references in the introduction). This could bias our estimate of the bioeconomic congestion effect towards zero. Nevertheless, it is important to note that transgenic corn was widely available and adopted in the years covered by the data, which we argue decreases the likelihood of highly dynamic behavioral feedbacks and belief-updating, e.g. as considered by Aldana et al. (2012). In any case, future research combining entomological pest density data with farmer pest control decisions could disentangle bioeconomic and behavioral feedbacks. Our research suggests this would be a worthwhile effort.

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 obviously correlated with area-wide adoption and hence with associated pest suppression spillovers. 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. Our research not only raises this as a potential source of bias, but also suggests a possible solution: Estimate the two-stage endogenous sorting model described above to generate predicted farmer-level adoption probabilities, controlling for selection *and* area-wide 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 demands significant demands on the data for achieving sufficient statistical power, we reserve such an exercise for future work with richer data.

References

Aldana, U., B. Barham, J. Foltz, and P. Useche. 2012. “Early adoption, experience, and farm performance of GM corn seeds.” *Agricultural Economics* 43(SUPPL. 1):11–18.

Aldana, U., J.D. Foltz, B.L. Barham, and P. Useche. 2011. “Sequential Adoption of Package Technologies: The Dynamics of Stacked Trait Corn Adoption.” *American Journal of Agricultural Economics* 93(1):130–143.

Ayer, H.W. 1997. “Grass Roots Collective Agricultural Opportunities.” *Journal of Agricultural and Resource Economics* 22(1):1–11.

Banzhaf, S.H., and R.P. Walsh. 2008. “Do People Vote with Their Feet? An Empirical Test of Tiebout’s Mechanism.” *American Economic Review* 98(3):843–863.

Bayer, P., N. Keohane, and C. Timmins. 2009. “Migration and hedonic valuation: The case of air quality.” *Journal of Environmental Economics and Management* 58(1):1–14.

Bayer, P., and C. Timmins. 2007. “Estimating Equilibrium Models of Sorting across Locations.” *The Economic Journal* 117(518):353–374.

Bayer, P., and C. Timmins. 2005. “On the equilibrium properties of locational sorting models.” *Journal of Urban Economics* 57(3):462–477.

Berry, S., J. Levinsohn, and A. Pakes. 1995. “Automobile Prices in Market Equilibrium.” *Econometrica* 63(4):841–890.

Berry, S., O.B. Linton, and A. Pakes. 2004. “Limit Theorems for Estimating the Parameters of Differentiated Product Demand Systems.” *Review of Economic Studies* 71(3):613–654.

Birol, E., E.R. Villalba, and M. Smale. 2008. “Farmer preferences for milpa diversity and genetically modified maize in Mexico: a latent class approach.” *Environment and*

Development Economics 14(4):521.

Brito, D.L., E. Sheshinski, and M.D. Intriligator. 1991. "Externalities and compulsary vaccinations." *Journal of Public Economics* 45(1):69–90.

Brock, W.A., and S.N. Durlauf. 2001. "Discrete choice with social interactions." *The Review of Economic Studies* 68(2):235–260.

Culliney, T.W. 2014. "Crop Losses to Arthropods." In *Integrated Pest Management*. Dordrecht: Springer Netherlands, pp. 201–225.

Dubé, J.-P., J.T. Fox, and C.-L. Su. 2012. "Improving the Numerical Performance of Static and Dynamic Aggregate Discrete Choice Random Coefficients Demand Estimation." *Econometrica* 80(5):2231–2267.

Fernandez-Cornejo, J., and S. Wechsler. 2012. "Revisiting the impact of Bt corn adoption by U.S. farmers." *Agricultural and Resource Economics Review* 41(3):377–390.

Florax, R.J.G.M., C.M. Travisi, and P. Nijkamp. 2005. "A meta-analysis of the willingness to pay for reductions in pesticide risk exposure." *European Review of Agricultural Economics* 32(4):441–467.

Foster, A.D., and M.R. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy* 103(6):1176–1209.

Foster, A.D., and M.R. Rosenzweig. 2010. "Microeconomics of Technology Adoption." *Annual Review of Economicsview of economics* 2.

Gerpacio, R. V, J.D. Labios, R. V Labios, and E.I. Diangkinay. 2004. *Maize in the Philippines: Production Systems. Constraints, and Research Priorities*. CIMMYT.

Grogan, K.A., and R.E. Goodhue. 2012. "Spatial externalities of pest control decisions in the

California citrus industry." *Journal of Agricultural and Resource Economics* 37(1):156–179.

Hicks, R.L., W.C. Horrace, and K.E. Schnier. 2012. "Strategic substitutes or complements? The game of where to fish." *Journal of Econometrics* 168(1):70–80.

Hutchison, W.D., E.C. Burkness, P.D. Mitchell, R.D. Moon, T.W. Leslie, S.J. Fleischer, M. Abrahamson, K.L. Hamilton, K.L. Steffey, M.E. Gray, R.L. Hellmich, L. V Kaster, T.E. Hunt, R.J. Wright, K. Pecinovsky, T.L. Rabaey, B.R. Flood, and E.S. Raun. 2010. "Areawide suppression of European corn borer with Bt maize reaps savings to non-Bt maize growers." *Science* 330(6001):222–225.

Janssen, S., and M.K. van Ittersum. 2007. "Assessing farm innovations and responses to policies: A review of bio-economic farm models." *Agricultural Systems* 94(3):622–636.

Kathage, J., and M. Qaim. 2012. "Economic impacts and impact dynamics of Bt (Bacillus thuringiensis) cotton in India." *Proceedings of the National Academy of Sciences of the United States of America* 109(29):11652–6.

Klaiber, H.A., and D.J. Phaneuf. 2010. "Valuing open space in a residential sorting model of the Twin Cities." *Journal of Environmental Economics and Management* 60(2):57–77.

Koster, H.R.A., J. van Ommeren, and P. Rietveld. 2014. "Agglomeration economies and productivity: A structural estimation approach using commercial rents." *Economica* 81(321):63–85.

Lee, J.C., H.J. Burrack, L.D. Barrantes, E.H. Beers, A.J. Dreves, K.A. Hamby, D.R. Haviland, R. Isaacs, T.A. Richardson, P.W. Shearer, C.A. Stanley, D.B. Walsh, V.M. Walton, F.G. Zalom, and D.J. Bruck. 2012. "Evaluation of Monitoring Traps for <I>Drosophila suzukii</I> (Diptera: Drosophilidae) in North America." *Journal of Economic Entomology*

105(4):1350–1357.

Maertens, A., and C.B. Barrett. 2013. “Measuring Social Networks’ Effects on Agricultural Technology Adoption.” *American Journal of Agricultural Economics* 95(2):353–359.

Mendoza, M.S., and M.W. Rosegrant. 1995. “Pricing Behavior in Philippine Corn Markets: Implications for Market Efficiency.” *Research Report- International Food Policy Research Institute*:11–79.

Miranowski, J.A., and G.A. Carlson. 1986. “Economic issues in public and private approaches to preserving pest susceptibility.” In *Pesticide resistance: Strategies and tactics for management*. National Research Council, National Academy Press Washington, DC, pp. 436–448.

Morallo-Rejesus, Belen G. Punzalan, E. 2002. “Mass Rearing and Field Augmentation of the Earwig, Euborellia Annulata, against Asian Corn Borer.”

Mutuc, M., and R. Rejesus. 2012. “Which Farmers Benefit the Most from Bt Corn Adoption in the Philippines? Estimating Heterogeneity Effects.” In *International Association of Agricultural Economists Triennial Conference*. Foz do Iguacu, Brazil, pp. 18–24.

Oerke, E.-C. 2005. “Crop losses to pests.” *The Journal of Agricultural Science* 144(1):31.

Qiao, F. 2015. “Fifteen Years of Bt Cotton in China: The Economic Impact and its Dynamics.” *World Development* 70:177–185.

Sanglestsawai, S., R.M. Rejesus, and J.M. Yorobe. 2014. “Do lower yielding farmers benefit from Bt corn? Evidence from instrumental variable quantile regressions.” *Food Policy* 44:285–296.

Schelling, T.C. 1971. “Dynamic models of segregation.” *Journal of Mathematical Sociology* 1(2):143–186.

Schelling, T.C. 1969. “Models of segregation.” *The American Economic Review* 59(2):488–493.

Songsermsawas, T., K. Baylis, A. Chhatre, and H. Michelson. 2016. “Can Peers Improve Agricultural Revenue?” *World Development*.

Timmins, C. 2007. “If you Cannot Take the Heat, Get out of the Cerrado? Recovering the Equilibrium Amenity Cost of Nonmarginal Climate Change in Brazil.” *Journal of Regional Science* 47(1):1–25.

Timmins, C., and J. Murdock. 2007. “A revealed preference approach to the measurement of congestion in travel cost models.” *Journal of Environmental Economics and Management* 53(2):230–249.

Useche, P., B.L. Barham, and J.D. Foltz. 2009. “Integrating Technology Traits and Producer Heterogeneity: A Mixed-Multinomial Model of Genetically Modified Corn Adoption.” *American Journal of Agricultural Economics* 91(2):444–461.

Vacher, C., D. Bourguet, M. Desquilbet, S. Lemarie, S. Ambec, and M.E. Hochberg. 2006. “Fees or refuges: which is better for the sustainable management of insect resistance to transgenic Bt corn?” *Biology Letters* 2(2):198–202.

WSJ. 2016. “Behind the Monsanto Deal, Doubts About the GMO Revolution.” *The Wall Street Journal*.

Xu, Z., D. a. Hennessy, K. Sardana, and G.C. Moschini. 2013. “The realized yield effect of genetically engineered crops: U.S. maize and soybean.” *Crop Science* 53(3):735–745.