ABSTRACT

CONNOR, LAWSON QUINN. Post-Adoption Impacts of GM Corn on Farm Decisions in the Philippines. (Under the direction of Dr. Roderick Rejesus and Dr. Zachary Brown).

The impacts of GM crops in agriculture have been numerous, and the studies of these impacts have been vast as well. However, while the direct economic and agronomic benefits of these crops have been accounted for in the literature, less has been done to understand the impact that these benefits can have on decisions made by agents in these agricultural systems where adoption has taken place. In this dissertation, two specific issues are explored, the effect that adoption has on the adopting farm. The specific issue of the adoption effects on labor time allocation is investigated here. Additionally, the effect of GM corn adoption on the decisions of non-adopting farms is also explored.

GM corn, particularly varieties that reduce or even eliminate pest damage, can have local (on the farm) and area-wide effects. Pesticidal effects of some GM crops reduce pest pressure, for adopting and potentially non-adopting farms as well. This can reduce associated labor needs on the adopting farm. However, pest reduction can also affect the distribution of yield, which, on its own, can induce changes to input use (including labor time) on the farm. This latter issue, if it affects labor time, produces a competing effect to the labor savings induced by adoption. The strength of this feedback mechanism from changes to the distribution likely depends on the specific changes to the distribution produced by the GM variety and the characteristics of the farmer and environment in which adoption took place. This says that the effect of adoption on farmer behavior, relating to labor decisions is likely context specific. This is an important issue since understanding the mechanisms driving changes post adoption greatly informs policy decisions related to the introduction and

regulation of GM varieties. In addition, we able to identify responses to risk and mean incentives separately, having two varieties that affect either the mean or the variance but not both. This allows us to infer the relative importance of these two channels to farmers, which also informs policy makers of key incentive drivers where agricultural sector development is the primary policy goal. We find that GM crops are associated with increases in labor time at pre-harvest as well as at harvest time and that farmers in the sample used (typically poorer farmers with farm sizes less than 2 hectares on average) are more sensitive to risk than to changes in the mean.

Since the pest reducing effects can potentially spillover to neighboring farms, interactive decision mechanisms can also exist. These neighboring farms can avoid the cost of adoption themselves while still receiving the pest reduction benefits. This public good provision by adopting farms can be observed as a reduction in adoption incentive for neighboring farms. This issue is also explored and the significance of this issue is largely rooted in the welfare analysis associated with Bt crops. Findings show that welfare analysis should take into account adopting as well as non-adopting farmers since both experience impacts from Bt being planted in the area. Identification of this effect relies on an instrumental variables method introduced in Bayer and Timmins (2007) since the share of adoption in an area is endogenous with individual decisions to adopt in the non-experimental sample used here. Findings suggest that increases in area-wide adoption rates decreases individual adoption incentives in the sample used for this study. We take care to inform the reader of the institutions and conditions of farmers in the sample to enhance the ability to interpret our results.

Post-Adoption Impacts of GM Corn on Farm Decisions in the Philippines.

by
Lawson Quinn Connor

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APPROVED BY:

Roderick Rejesus Committee Co-Chair	Zachary Brown Committee Co-Chair
Barry Goodwin	Roger Von Haefen

DEDICATION

To my mother. My rock, my support and my constant motivator throughout this process and in life. To Terry Saario and Lee Lynch for their guidance, inspiration and friendship since the day our paths first crossed. And to my family in Antigua who remain my foundation.

BIOGRAPHY

Lawson Quinn Connor was born in the sunny twin island nation of Antigua and Barbuda in the West Indies. After completing his education at the Antigua Grammar School, he received a scholarship to attend Lester B. Pearson College of the Pacific to pursue an International Baccalaureate (IB) diploma. It was here that he was first introduced to, and developed an interest in Economics. After completing his education at Pearson, he was awarded another scholarship to attend Macalester College in St. Paul, Minnesota where he would earn his Bachelor of Arts degree in Chemistry with a minor in Economics. After returning home and working as a high school chemistry teacher for two years, he decided to finally pursue a career in Economics. Upon his acceptance to the Master's program at North Carolina State University, he decided to continue his education there by going on to obtain his Ph.D.

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CHAPTER 1

Introduction

Bt (Bacillus thuringiensis) corn was introduced in Philippines in 2003 as a means of improving the productive capacity of the agricultural sector in the Philippines, thereby reducing the import bill for yellow corn. Yellow corn is primarily used as livestock feed and is the second most important commercial crop in the Philippines after rice. This means that the potential enhancements from GM corn production in the Philippines are likely to be economically significant. Without a doubt, much interest exists in determining the effectiveness of Bt corn in improving corn production, improving farm(er) livelihood and reducing the reliance on import markets for yellow corn.

To this end, numerous impact studies have shown that Bt crops increase yield (Fernandez-Cornejo and Wechsler 2012; Qaim and Zilberman 2003; Sanglestsawai, Rejesus and Yorobe 2014b), decrease variance (Liu 2012; Shi, Chavas and Lauer 2013; Chavas and Shi 2015), increase farm income (Kathage and Qaim 2012; Kouser, Qaim and Abedullah 2015a; Qaim 2010), increase income in the local economy (Raybould and Quemada 2010; Qaim et al. 2006; M Qaim 2009a; Kathage and Qaim 2012), decreases pesticide use (Raybould and Quemada 2010), and has effects on the local labor market (Kathage and Qaim 2012). One issue that the literature has made clear is that the overall impact of GM crops varies greatly across the specific context of adoption (Qaim et al. 2006). Several meta-analyses have shown that considering Bt as either yield increasing or insecticide reducing will largely depend on the magnitude of use of insecticides by farmers prior to adoption.

Farmers previously using high amounts of insecticide experience little yield increases, but significant reductions in pesticide use. The converse is true for farmers who typically had low pesticide usage prior to adoption (Areal, Riesgo and Rodríguez-Cerezo 2012). Labor-saving features of GM crops have also been shown to vary vastly depending on where the technology is adopted. Other work has also shown that adoption of Bt can have effects on farms in an area, even those that have not adopted the technology. One such impact is the reduction of target pests on non-adopting plots, in addition to those that have adopted. These imply that welfare assessments in this context are difficult to perform without an understanding of the context and the mechanisms that drive incentives post adoption. This dissertation explores two cases where post-adoption feedbacks are important in explaining final outcomes. An understanding of the mechanism producing these outcomes is also important in performing accurate welfare analyses. The first issue explored is an investigation of the mechanism that drives farm labor time incentives post adoption of GM corn in the Philippines. The second issue explored is the impact that adoption can have on non-adopting farmers in the same area.

The dissertation is organized into three main chapters. Chapter 2 introduces the context of agriculture in the Philippines, with a focus on corn farmers and, in particular, commercial yellow corn farmers in the Philippines. It describes the characteristics of these farms, such as incomes and typical input use. The chapter also lays out the institutional/government environment surrounding the farmers, the available infrastructure and support by the government and local agricultural organizations. The location of these farms is also discussed accompanied by a discussion of location specific characteristics such as local climate, cropping seasons and access to primary markets for sale of corn. The chapter concludes with a discussion of the sample used for chapters 3 and 4 of this dissertation, and draws on the prior discussion to place the data in context in the Philippines.

Chapter 3 explores the mechanism through which changes to the distribution of yellow corn yield, experienced upon adoption of GM crops, can affect labor choices made by the adopting farmer. A theoretical framework is developed which recognizes the labor-saving features of the pest eliminating GM varieties but also accounts for shifts to incentives produced from changes to the distribution of yield. The framework establishes the context specific nature of the effects of GM adoption and is used to interpret empirical findings. The data used contains observations of farmers who have adopted two GM varieties (and a non-GM hybrid variety). A Bt variety, which primarily affects yield by increasing mean outcomes, but has minimal effects on the variance and other extremes of the distribution. Also present is a Bt/HT (stacked) variety that primarily affects the variance of the distribution and has little effect on the mean of the distribution. The empirical strategy exploits these differences in the effect of the two GM varieties on the distribution of yield to uniquely identify responses to both the risk and mean impact channels. The findings in this chapter show that changes to the mean has different effects on labor decisions in the pre-harvest and harvest phases of production than do changes to the variance (risk) of yield. It also shows that low income farmers (the type represented in the sample) are more sensitive to changes in their risk exposure, than they are to changes in mean outcomes.

Chapter 4 introduces a methodology commonly used in the hedonic literature to identify an endogenous area-wide effect associated with large scale adoption of Bt corn. Research has previously found that as the rate of Bt adoption increases in an area, this can directly affect (decrease) the level of pest pressure in an area. This decrease in pest pressure is shown to exist not only on adopting farms, but on non-adopting farms as well. This sets the motivation of the investigation as Bt seeds are costlier that traditional hybrid varieties (as much as three times as much in the sample observed for this study). Farmers have incentive to free-ride on the provision of damage abatement (through pest pressure reduction) and avoid the cost of individual abatement. However, identifying this reduction in incentive to adopt presents estimation challenges since the observation of equilibrium adoption rates is endogenous because of its correlation with individual decisions to adopt. The instrumental variables method introduced in Bayer and Timmins (2007) is used here to identify the effect. The method uses variation of exogenous characteristics, correlated with individual and area level adoption, but uncorrelated with pest pressure and other unobserved factors to form instruments. The results in this chapter show that indeed, the disincentive is present. This suggests that these spillovers are important to account for in welfare analyses given that the welfare of farmers not adopting Bt are also affected by other farmers' adoption decisions.

This research highlights the complex nature inherent in Bt adoption systems. Incentive shifts are apparent through own adoption of GM varieties because of their effect on other outcomes of interest to the farmer such as income and risk exposure. Incentive shifters also spillover to nearby farmers because of area level impacts that can exist, such as reductions in pest pressure. These adjustments that take place post adoption of GM varieties, which may not be initially apparent can confound the recovery of accurate welfare estimates when conducting impact assessments.

CHAPTER 2

Institutional Overview of Corn Production in the Philippines

2.1. Introduction

Corn is produced all over the globe. However, corn production environments and practices typically vary across different countries. Even though there are general production practices that all countries follow, each corn-producing country still has its own production idiosyncrasies. Thus, it is important to first understand the specific corn production context of a country, before presenting analysis that determine how adoption of genetically modified (GM) corn behaviorally affects production decisions of farmers in that particular country. As such, the objective of this chapter is to provide information and background on the unique characteristics of corn production in the Philippines, as well as the physical and institutional environment under which corn producers in the country operate. In addition, given our interest in GM corn, a brief historical overview of the evolution of GM corn use in the Philippines is also discussed.

In the Philippines, corn is the second most important crop after rice, with approximately one-third of Filipino farmers (~1.8 million) depending on corn as their major source of income. The "white" corn type (usually for food consumption) was planted on most corn area at 67.23% nationally, and the remainder of corn area in the Philippines (32.77%) was used for planting the "yellow" corn type (primarily intended for livestock feed use).

Note that the yellow corn type is the one considered in this dissertation (and is the type grown in the chosen study areas).

The two Chapters that follow in this dissertation use data from two high producing corn provinces in the Philippines, Isabela and South Cotabato. Isabela is located in the Northern island group of Luzon while South Cotabato is located in the island group of Mindanao in the south Figure 2.1). Data from these two areas were used as they provide a broad spectrum of the commercial farming culture and environments faced in the Philippines. The following discussion, provides a discussion that will help in understanding the institutional environment in the Philippines and the areas where the data used in this dissertation were generated. Our discussion serves primarily to permit understanding and interpreting the results presented in subsequent chapter.

2.2. Philippine Corn Production Environments: A Nationwide Overview by Topography Type

In the Philippines, corn production is normally grouped into three primary topography types: (1) lowlands, (2) upland plains, and (3) rolling-to-hilly areas. Corn produced in these three topographies are still usually grown rain-fed. In the lowlands, corn is typically grown as a dry season crop (October/November to February), with rice being planted in the wet season (March/April to August). Corn is typically planted from October to December in the lowlands, with the exception of lowland areas in the Northern provinces of the main

Philippine island group (called Luzon) [1] where corn is grown as the primary crop instead of rice. For the cropping season starting in October to December, 70%-100% of farmland located in the lowland regions is used for corn, even in the Southern parts of the Luzon island group, where rice typically serves as the primary crop.

Most farming in the lowland areas is dependent on rainfall (i.e., rain-fed), with very few farmers having their own irrigation systems. Most farmers in these areas have shifted away from traditional corn varieties, and almost exclusively use hybrid corn seeds. There are typically no easily-accessible, nearby primary markets in the villages around major corn growing areas in the lowlands. Farmers in these areas usually sell their corn to secondary markets, or private traders, who come from an average of 35 kilometers (km.) away to pick up the corn from the farms or in a central location in the village. Transportation is available in the lowlands, but mostly during good weather as villages are only accessible through seasonal rough roads.

Corn production in the upland plains regions are primarily found in the Luzon and Mindanao island groups of the Philippines. Corn farmers in the upland plains typically have 2-3 cropping seasons per year. Corn is commonly grown in two cropping seasons in at least 75% of the cultivated upland plains area, with the second corn cropping (typically, dry season) intercropped with vegetables. In some of these upland plain areas, a third cropping of corn, intercropped with tobacco or mung bean, can be grown with sufficient rainfall and

[1] The Luzon island group is one of three main island groups in the Philippines. The other two island groups are Visayas and Mindanao. Note that Luzon is typically considered the "main" island group as it is where the nation's capital (Manila) is located. Geographically, Luzon is in the Northern part of the nation, Visayas in the middle, and Mindanao in the South.

favorable weather conditions. The upland plain regions in Luzon, especially in the Northern provinces where one of our study area is located (e.g., Isabela province), are generally closer to primary and secondary markets than the upland plain regions in Mindanao (where our second study area is located – South Cotabato province) (Gerpacio et al. 2004).

The rolling-to-hilly areas are the most common type of corn farmland in the Philippines, and is also commonly found in Luzon and Mindanao. Like the upland plains regions, the weather in the rolling-to-hilly areas allow for two cropping seasons per year, with a third potentially occurring in particularly good rainfall years. Farmers in these areas often grow two crops of corn, with a few farmers planting a third crop of corn intercropped with legumes, vegetables, or a combination of these. For example, in the Northern provinces of the Luzon island group (e.g. Isabela province), about 85% of the cultivated corn land in the rolling-to-hilly areas had two corn growing cycles in the year, using legumes in the third cropping cycle (Gerpacio et al. 2004). In Cebu, a major province in the Visayas island group, at least 90% of the cultivated corn land in the rolling-to-hilly agro-ecozone is devoted to corn in the first season (wet season), with a few farmers intercropping with legumes.

In most rolling-to-hilly areas of the Philippines, high rainfall and some typhoons still occur in the second cropping (dry season). Therefore, more farmers in the rolling-to-hilly areas intercrop vegetables and other cash crops with corn for the second cropping, although some still solely plant a corn crop. With intercropping in these rolling-to-hilly areas, corn is planted in only 50-75% of the total cultivated area. In the Southern island group of Mindanao, for example in Bukidnon province, farmers in rolling-to-hilly areas consider rice and vegetables as the second and third most important crops after corn. Hence, rice and vegetable crops are usually intercropped with corn for the second cropping period (i.e., with rice often planted in a separate parcel of land). Moreover, farmers in Mindanao (especially in South Cotabato province) plant a third corn crop, which sometimes fail due to unfavorable weather. Some farmers in the rolling-to-hilly agro-ecozone of the Visayas island group, on the other hand, fallow their fields during the third cropping to avoid crop failure. In addition, farmers in the rolling-to-hilly areas in the Mindanao island group estimate that 63% to 85% of their cultivated area is grown to corn, while the rest may be planted to rice, peanut, cotton, and sugarcane.

Soil erosion is common in the rolling-to-hilly corn zones due to the sloped environment. Most corn-producing villages are also only generally accessible by gravel roads. Nevertheless, public transportation is still typically available in these areas. Corn grown in these rolling-to-hilly areas may be for home use or cash, and the types of corn planted will be determined by the end use (white vs. yellow). In the rolling-to-hilly areas of Luzon and Mindanao island groups, yellow corn intended for livestock feed is grown primarily for income, and improved open-pollinated varieties (OPVs), hybrids, and more modern varieties (e.g., GM varieties) are preferred in these areas. This contrasts with the rolling-to-hilly areas of Cebu and Leyte (i.e., major corn producing provinces in the Visayas island group), where white corn is mainly grown and is used for household consumption. In this case, traditional varieties that require fewer inputs and management are more commonly utilized in the Visayas island group instead.

Note that weather variations may also help explain some of the differences in crop choice and degree of commercialization across areas with the rolling-to-hilly topography.

Typhoons, tropical storms, and/or flooding affect many areas of the Philippines, but these weather events more acutely affect the rolling-to-hilly areas in the Visayas island group. In contrast, the rolling-to-hilly areas in the Northern provinces of Luzon (e.g., Isabela) and the corn-producing provinces in Mindanao, are less susceptible to typhoons than comparable areas in Visayas. Moreover, tropical storms are rarer still in the Mindanao island group.

2.3. Corn Production Tasks and Practices in the Philippines: A Brief Background

Producing corn in the Philippines (and in most places) starts with land preparation. Land preparation for corn production consists of one or two plowing operations, harrowing to level the field and reduce the size of soil clods, and furrowing. The timing of these operations depends on soil moisture conditions. The first plowing is generally done soon after harvesting the previous crop to prevent weed growth and incorporate residues. These land preparation operations are often done with animal power, but may be mechanized on level terrain, especially if capital is available to pay for tractor rental.

In the lowlands, the corn field is plowed once and harrowed twice to prepare the land for the dry season corn crop, after wet season rice is harvested. The extent of farm mechanization is 70-95% (usually during land preparation), and farmers cite heavy labor use (both family and hired labor) during planting and harvesting. Furrowing is immediately followed by sowing and basal fertilizer application.

Inorganic fertilizers are generally applied 25-30 days after planting in the lowlands. Some farmers also use chemical pesticides to control insect pests. Off-barring, hilling-up, and manual/hand weeding are practiced to control weeds. Harvesting, dehusking, drying, and sometimes shelling is done manually with both family and hired labor.

In the upland plains where corn mono-cropping is practiced, plowing is generally mechanized, while animal draft power is used in harrowing and furrowing. The field is plowed two to three times and harrowed once or twice depending on soil conditions. Furrowing is done at planting. For farmers planting corn hybrids in the upland plains, one seed per hill is sown at a distance of 60-75 cm between furrows and 20-25 cm between hills. For farmers planting OPV corn, two seeds per hill are sown at 60 cm between furrows and 30-40 cm between hills.

Weeds are commonly controlled through combined manual (or hand) weeding and off-barring and hilling-up at 20-25 days after planting in the upland plain areas. Herbicides are very seldom used, although in the upland plains of Northern Luzon (e.g., Isabela) pre- and post-emergence herbicides may be applied when labor is scarce. Fertilizers and pesticides are also applied in the upland plains, but often at rates lower than what is recommended or required by the crop. Most farmers have been introduced to integrated pest management (IPM) technology in the upland plains, but its use has been limited. For example, farmers were trained in the use of Trichogramma (i.e., a biological control for Asian corn borer (ACB)), yet in only a few places is it actually used in upland plains area. Corn farmers in the upland plains reported “limited availability” constrained their use of the aforementioned biological pesticide. Harvesting is usually done manually in the upland plains.

In corn areas with rolling-to-hilly topographies, land preparation is done manually or with the use of a draft animal. Other crop management practices are similar to those in the upland plains, although input use in rolling-to-hilly areas located in the Visayas island group (particularly in Cebu and Leyte province) is normally lower than the input levels used in the upland plains areas in Luzon and Mindanao. Corn farmers in rolling-to-hilly areas in the Visayas grow mostly local/traditional varieties, sown three to five seeds per hill at distances of 30 cm x 60 cm, 45 cm x 45 cm, or 50 cm x 100 cm. Farmers use wider planting distances than when planting improved OPVs or hybrids in other topographical environments (i.e., primarily to accommodate intercrops). The average labor use of corn farmers in the rolling-to-hilly areas of corn production does not differ much as compared to the other topographical environments in the Philippines.

On a nationwide basis, the typically suggested fertilizer recommendation for corn in the Philippines is as follows: 100 kg/ha urea (45-0-0) plus 200 kg/ha complete fertilizer (14-14- 14) for OPVs, and 150 kg/ha urea plus 300 kg/ha complete fertilizer for hybrids. Complete fertilizer is used for basal application, while urea is applied as side dressing 25-30 days after planting. Based on these national recommendations, the fertilizer application rates typically used by farmers in the upper plains and rolling-to-hilly areas of Luzon and Mindanao are sufficient (e.g., corn in the provinces of Isabela, Bukidnon, South Cotabato, and Cotabato). Corn farmers, however, tend to apply more urea (at 150-325 kg/ha), and less complete fertilizer (at 50-325 kg/ha) in these areas.

The benefits of proper fertilizer recommendations are not realized in many corn producing regions in the Philippines. While farmers in Southern Luzon provinces may overuse fertilizers for their maize (at 100-600 kg/ha urea plus 150-350 kg/ha complete fertilizer), those in the rolling-to-hilly areas of the Visayas island group do not apply enough fertilizer. Only a few farmers in the upland plains and rolling-to-hilly areas use organic fertilizers (particularly farmyard manure), and lime to address soil acidity problems. Farmers in the hybrid growing areas commonly use pesticides for insect control, while those in the white corn consuming areas of Visayas do not. Farmers who do use pesticides in most corn producing regions, however, state that they apply minimal amounts and only when infestation is heavy.

In general, post-harvest operations in corn production involve: shelling, solar drying, and milling. Shelling is typically done through the use of mechanical shellers, even though manual shelling is also practiced in some areas (i.e., in the Visayas where grain is for home use). use of mechanical shellers typically cost PhP8-20.00 (US$0.16- 0.40)/50-kg sack (Gerpacio et al. 2004). After shelling, the corn is then sun-dried for 2-3 days on multipurpose cement pavements. Farmers report paying anywhere from the minimal PhP0.50 to as high as PhP16.00 (US$0.01-0.32)/50-kg sack of corn for the use of these pavements. Due to lack of drying facilities, local roads and highways are commonly used as drying pavements during peak harvest season. In Visayas, corn is dried in the husk to allow for longer storage (i.e., since corn is mostly for home consumption), whereas corn grain in Luzon and Mindanao is sold immediately after drying to eliminate the need for storage. Milling is practiced only in locations where corn was for home use (e.g., Visayas). In these areas, corn grain is milled in batches whenever needed and stored for a certain period.

2.4. Profile of Philippine Corn Farms and Farmers

2.4.1. Socio-Demographic Characteristics

The average age of corn farmers in the Philippines in 2009 was 51 years, with 92% of them male.[2] The typical male corn farmer in the Philippines was, on average, 5 years younger than the average female farmer (PSA, 2013). Farmers in the 41-50 age range were the largest group of corn farmers in the Philippines in 2009 at 32.42% (PSA, 2013), followed by farmers in the age range of 51-60 at 28.12%.

On average, 45.68% of Philippine corn farmers had some form of elementary education in 2009 (PSA 2011, 2014) . However, only 22.07% finished elementary education. In addition, 11.03% and 2.83% of Philippine corn farmers graduated from secondary (high school) and tertiary (college) levels of education, respectively. About 3.48% of Philippine corn farmers had no schooling at all. Children's education however, is regarded by many in the Philippines as a top priority. This also applies to many farmers who try to ensure that their children are able to receive an education which will give them access to income earning opportunities off the of the farm. This is the case even among low income farmers who often sell livestock at the beginning of the school year to pay for related expenses (Gerpacio 2004). Effort on the farm is therefore seen, in part, as a means to provide opportunities for the upcoming generation.

[2] As discussed in the next two chapters of this dissertation, the data utilized to analyze the effects of GM corn adoption on production decisions is based on survey data collected in the Philippines in crop year 2007 and 2011 (for wet season). Therefore, in this section, we report pertinent, nationally-representative statistics about Philippine corn farms and farmers in 2009 because this year bisects the two years for which we have survey data. Note that in this section we mainly use statistics from reports written by the Philippine Statistics Authority (PSA) in 2011 and 2013 (where profile data for 2009 was mostly reported) (PSA, 20011 and 2013).

Nationally, 93.26% of Philippine corn farmers reported their main occupation to be "farming", with the average level of farming experience among all farmers in 2009 being 22 years. The average farm size for all farms in the Philippines was 2.19 hectares (ha.) in 2009. The average corn farm on the other hand was 1.27 ha., ranging from less than 1 ha. to approximately 4 ha. Most corn growers in the Philippines are small, semi-subsistence farmers.

With regards to farm ownership, about 47% of corn farm parcels in the Philippines is fully owned by the farmer. About 23.06% were tenanted, 14.90% were rent-free (farmers who were allowed to use land without a rental obligation), 6.70% percent were leased/rented, and 3.82 percent were held under Certificate of Land Transfer (CLT) and Certificate of Land Ownership Award (CLOA)[3]. Most fully owned corn farm parcels are found in the Northern provinces of Luzon. On the other, corn farm land in the Visayas island group is mostly tenanted.

2.4.2. Material Input Use and Cost of Production Profile

In 2009, inorganic fertilizer and hired labor on average had the largest portion of the average variable cost for corn production in the Philippines at 27% and 25%, respectively (PSA, 2011). Average variable costs for corn production were PhP (Philippine peso) 26,679 per ha. (or 78% of all costs), while fixed costs were PhP7,318 per hectare. Typical rental value of corn land is P3,139, and is around 43% of the total fixed costs.

[3] A CLT recognizes the formal transfer of ownership from one party to another. No payment is required in this scheme. A CLOA is awarded under the 1988 Comprehensive Agrarian Reform Program (CARP) whose intent is to increase land holdings by the traditionally landless. Tenant farmers are allowed to apply for a CLOA which must be approved by the Department of Agrarian Reform (DAR). Land owners and tenants typically try to reach an agreement on land valuation and payments required for the transfer.

Seed, fertilizers, and pesticides are the most common material inputs bought by Philippine corn farmers. Seeds of local/traditional varieties and improved OPVs are often recycled or exchanged with other farmers within corn-producing villages. If bought, seed of local/traditional varieties costs anywhere from PhP10-36/kg (US$0.50-0.72/kg) in the Visayas island group, to PhP4.50-7.20/kg (US$ 0.09-0.14/kg) in Mindanao, while that of the local/improved OPVs ranged from PhP3-30/kg (US$ 0.06-0.60/kg) across the different growing areas (Gerpacio et al. 2004, 2004; PSA, 2011). Nationally, corn hybrid seed price ranged from PhP1,500-2,225/bag or about PhP80-125/kg (US$ 0.10-0.12/kg).

Among those Filipino corn farmers who planted yellow corn, 23.01% used hybrid seeds, 7.73% local/traditional seeds, and 1.37% OPV seeds. In contrast, for corn producers who plant white corn, 64.15% use local/traditional seeds, 2.32% use OPV seeds, and 1.42% use hybrid seeds. Hybrid seeds is more popularly used by corn farmers in the Central to Northern provinces of Luzon. The use of local/traditional corn seeds was popular in the Visayas island group, with 98.33% of corn farmers using them.

In general, the cost of material inputs is a major concern for corn farmers in the Philippines, as is the timely availability of these inputs. Material farm inputs from agricultural supply dealers, agricultural cooperatives, and private traders are typically available across all corn-producing regions of the Philippines (Gerpacio et al. 2004). Corn farmers with adequate monetary resources buy material inputs directly from agricultural supply stores/dealers. However, some corn farmers report insufficient capital to directly purchase inputs, and instead obtain them from private trader-financiers who provide inputs on loan, with high interest rates (Gerpacio et al. 2004). This arrangement does not always allow farmers to choose among the material inputs available, e.g., fertilizers, pesticides, or even seed. With private trader-financiers, material inputs are often priced higher than the prevailing market retail price (from agricultural supply dealers).

Note that about 85.41% of hybrid corn seed users in the country obtain their seeds from private traders. On the other hand, about 5.10% of these corn farmers obtain hybrid seeds from the Department of Agriculture-Regional Field Unit (DA-RFU), and around 4.22% from Cooperatives. Hybrid corn seed users that acquired them from Local Government Units (e.g. municipal agricultural offices) and seed growers account are only about 2.99% and 2.11%, respectively.

Farmers who use recycled seed may have lower cost of production as they set aside their own planting materials, and the lack of capital at planting time may not seriously hamper their planting schedule. However, these corn farmers are aware that much lower yields are obtained from recycled seed, especially if no to minimal fertilizer is applied. Farmers' cooperatives are the optimal source of production inputs in most cases, but in the Philippines few are successful enough to support the needs of their members (Gerpacio et al. 2004).

2.4.3. Labor Use and Intensity Profile[4]

Overall, labor use for corn production in the Philippines ranges from a low of 28 person-days per hectare (PD/ha), in the generally mechanized upland plains of Mindanao (e.g. South Cotabato), to a high of 111 PD/ha in the rolling-to-hilly areas in the Visayas (e.g., in Cebu

[4] Given our interest in the labor use of effects of GM corn adoption (see next chapter of this dissertation), we spend some time here to provide more details about labor use and labor intensity across tasks. Information on labor costs and mechanization are also discussed in the next sub-section.

province where manual labor is mostly used). Women farmers (mostly hired labor), provide 10-45% of the total labor used in corn production nationally, and they are usually employed during planting, manual weeding and harvesting. Labor use and animal power use are highest in the rolling-to-hilly corn topography located in the Visayas island group (e.g., Cebu and Leyte).

In terms of labor intensity, land preparation tasks, as well as manual tasks such as weeding, tend to be the ones that utilize more labor in Philippine corn production (i.e., these tasks are typically very labor intensive). However, in some cases, wealthy farmers may be able to afford machinery such as mechanical plows, which reduces the labor intensity of these land preparation tasks. Nationally, 65.52% of corn farmers used combined man-animal power for plowing, while 12.63% utilized 4-wheel and 2-wheel tractors. In the case of harrowing, 45.38% of corn farmers utilized man-animal power and 7.56% used combined man-machine power. For furrowing 69.60% of farms used man animal while only 4.25% utilized man-machine labor.

As mentioned above, weeding is another corn production task that is, in general, considered a very labor intensive task. About 58.82% of corn farmers in the Philippines utilize of manual (or hand) weeding in their operations (Gerpacio et al. 2004). On the other hand, about 16.7% practiced chemical (herbicide) spraying, while 4.42% used mechanical weeding. Among the main corn producing areas in the Philippines, the highest percentage of corn farmers who performed manual weeding at 95.65% is located in the Southern provinces of Luzon. About 48.98% of farmers in the Northern provinces of Luzon sprayed chemicals/herbicides to control weeds in their farms.

One post-harvest task that is also typically considered as labor intensive is shelling. Across all corn growing regions in the Philippines, shelling of corn is done manually by around 52.73% of corn farmers, while the less labor intensive mechanical shelling approach is utilized by about 37.7% of corn farmers. Some 0.17% employed both methods. In Luzon, most corn farmers shelled corn manually (ie., greater than 95% of Luzon corn farmers). On average, the labor requirement for the more intensive task of weeding (and other pest management tasks) is about 15.62 man-days/ha. Harvesting operations for corn production in the Philippines typically require about 10.75 man-days/ha. Land preparation and planting operations on average require 8.46 man-days/ha and 6.38 man-days/ha, respectively. Post-harvest operations like manual shelling require about 3.25 man-days/ha, while mechanical shelling still requires about 1.3 man-days/ha. Solar drying of corn normally requires around 4.34 man-days/ha.

Aside from the amount of labor used for most corn productions tasks, it is also important to understand the variation in labor used: (1) by corn seed type, and (2) by labor source (i.e., hired vs. family labor). Labor use for corn farms that grow local/traditional corn varieties average around 54.45 man-days/ha. Farmers that use seeds of OPVs, on average, utilized 52.06 man-days/ ha, while farmers that plant corn hybrids used about 51.48 man-days/ ha. With regards to labor use by source, hired labor usage for corn production average around 24.18 man-days/ha (across all corn producing regions in the Philippines). On the other hand, operator and family labor on average contributed 12.69 man-days/ha. and 13.66 man-days/ha., respectively. Lastly, about 2.77 man-days/ha (on average) comes from exchange labor.

2.4.4. Labor Cost and Mechanization Profile

Philippine agricultural laborers hired for corn production operations typically receive wage rates in the following ranges (by island group): (a) PhP75-100 (US$1.50- 2.00)/person-day in Luzon, (b) PhP50-80 (US$1.00- 1.60)/person-day in Visayas, and (c) PhP60 85 (US$1.20- 1.70)/person-day in Mindanao. Both male and female agricultural laborers utilized by corn farms typically receive the same wage rate (i.e., there does not seem to be any observed gender bias in wage rates).

Snacks and/or lunch are sometimes also provided for these hired agricultural labor, especially during planting and harvest operations. Groups of farm laborers can also be contracted for either planting or harvesting corn. The typical contract arrangement is locally called the "pakyaw" system, where total labor is normally paid on a per hectare rate during planting. Harvesters are paid either in cash at per-sack rate or in kind, getting a share of the total harvested cobs. The most common harvest-sharing scheme is 10:1, where for every 10 sacks of harvested corn, the owner gets nine sacks and all the harvesters get one.

For land preparation, some corn farmers in major producing areas contract for the use of four-wheel tractors at a rate ranging from PhP650-1,200 (US$13- 24.00) per passing in the upper plains area of Northern Luzon (i.e., Isabela province) and Mindanao (South Cotabato and Bukidnon provinces). Draft animal power (i.e., water buffaloes) with operators can also be contracted for land preparation especially in hilly areas at PhP80-200 (US$1.60-4.00)/ person-animal day. However, in the upper plain areas of Mindanao (e.g., South Cotabato), the rental rate for draft animal power (with an operator) is typically about PhP125

(US$2.50)/person-animal day. Corn farmers who do not own draft animals can also rent them at PhP40-100 (US$0.80-2.00)/animal-day.

Nationwide, about 48.78% of corn farmers own water buffaloes (locally called "carabao") as the main source of draft animal power used for various farming operations. Around 11.12% and 6.44% of corn farmers in the Philippines had cattle and horse as work animals, respectively.

Ownership of farm machinery, such as 2-wheel and 4-wheel tractors, irrigation pumps, mechanical shellers, and grain dryers was reported by only 11.76% of corn farmers nationwide. Farmers who owned two-wheel tractors were 4.29% of corn farmers, and those who own irrigation pumps comprise 3.74%. There are around 2.10% of corn farmers who owned a mechanical sheller. Among different tools and implements, 90.08% of corn farmers in the Philippines owned and used large machetes (i.e., called the bolo), around 60.50% of corn farmers had a plow, about 42.77% owned a yoke, and approximately 35.47% owned a shovel (Gerpacio et al. 2004; PSA, 2011).

2.4.5. Corn Yield and Output Price Profile

Yields of hybrid corn grown in the Northern provinces of Luzon (e.g., Isabela) are usually higher than those in the main corn-producing regions in Mindanao (e.g., South Cotabato and Bukidnon). Farmers in South Cotabato cited soil acidity/infertility, lack of technical information and limited capital as being hindrances. Nationwide, corn farmers are aware that the productivity of their corn crops can still be improved and report several reasons for this supposed "yield gap." They claim that erratic, unpredictable weather conditions affect crop growth, and tropical storms, like those that often occur in the northern parts of Luzon can destroy crops. In the lowlands of Southern Luzon, weather extremes – heavy rains and flooding at the start of the wet cropping and drought toward the later stages of crop growth– can adversely affect production.

Secondly, farmers tend to use less than recommended amounts of fertilizers in a number of corn producing regions (i.e., upland plains and rolling-to-hilly areas) because some of them lack the capital to purchase the inputs. Thirdly, farmers cite soil acidity and declining soil fertility as a problem. In the rolling-to-hilly agro-ecozones, the continued loss of fertile topsoil due to erosion constrains production. Other common constraints stated by corn farmers include pest incidence, farmers' lack of or insufficient access to technical information or technology, and poor crop management practices. The average yield among the commercial yellow corn producing areas though (which includes South Cotabato), is higher than those of other non-commercial and white corn producing areas.

In general, the national yield of corn has been steadily increasing with yellow corn primarily driving this increase. In the period 1985 – 2001 white corn experienced little growth while yellow corn yield increased by a rate of 4.9% annually. This trend represents a shift away from white corn in some areas as well as increasing adoption of high yielding varieties (hybrid and GM varieties) by yellow corn farmers. Bucking this trend are the lowland areas where flooding has restricted expansion of yellow corn production.

Yields have steadily increased in Isabela and South Cotabato as well. In Isabela, farm acreage devoted to corn has actually declined in this period, as yield has risen, resulting from the reduction in area dedicated to white corn and yellow corn farmers adopting high yielding varieties. Isabela also ranked highest in average maize yield (yield per farm) in the

Philippines. As mentioned earlier though, South Cotabato tends to have lower yield levels among the high producing commercial yellow corn areas (though higher than other corn farming). This is partially due to the low rainfall, fertility and administrative constraints mentioned earlier. Differences in adoption rates across Isabela and Mindanao could be partially explained by these constraints. The Department of Agriculture Bureau of Plant Industry (Mamaril 2007) explains that low rainfall reduces yield of Bt and may even completely diminish the expected yield gains. Fertilizer costs for Bt farmers also represented the second highest cost after labor (Navarro and Hautea 2014) which may also increase the cost of adoption of in South Cotabato where farmers complained of poor soil fertility being an issue[5]. Despite this fact, adoption rates were well over 80% for the stacked variety in South Cotabato in the 2011 round of the data used for this study.

In terms of the output price of corn grains in the Philippines, corn output prices vary little within and across the major-corn producing regions. In general, corn grain prices are higher by at least PhP1.00/kg in the nearest markets than at the farm gate. Yellow corn (usually hybrids) commanded a higher price than white local/traditional corn in most corn producing regions, except in South Cotabato province in Mindanao. In these areas, prices of white corn ranged from PhP4.50-10.00 (US$0.09- 0.20)/kg as compared to only PhP3.50-9.00 (US$0.07- 0.18)/kg of yellow corn.

[5] Gerpacio et al. (2004) point out that educational differences across regions can also drive adoption rates. Educational attainment among commercial farmers tended to be high (with most farmers attending or completing at least a primary level of education) while in South Cotabato, the level of educational attainment is often lower.

Some farmers reported receiving higher prices when planting biotech corn. This would be related to the fact that grain quality is often a factor that is considered when corn is being sold in the market and GM corn, being protected from pests, would typically have better looking corn ears than the hybrid or traditional varieties. However, the ability to capture these higher prices will depend on direct access to primary markets. Farmers who sell to traders often receive lower prices and there is also seasonal variation for farmers without storage facilities as the price of corn is lowest at harvest time but increases further from harvest (Navarro and Hautea 2014).

2.4.6. Income/Wealth Profile of corn farmers

In the Philippines, corn farmers are normally classified by wealth class as either poor, medium-intermediate, or rich, with each group being characterized by such parameters as farm size, income by source, household size, and number of livestock owned (Gerpacio et al. 2004). The poor group is typically made up of corn farmers who are tenants or sharecroppers, with large households, and little or no education. If they own their land, these farmers tend to have small farms of up to (at most) 2.0 ha only. They also characteristically earn most of their income from maize production and other agricultural enterprises (usually as hired labor in other farms) rather than from non-agricultural or non-farm activities. These farmers earn an estimated 59-76% of their income from maize production and none from non-agricultural activities.

Meanwhile, the medium-intermediate farmers, many of whom own their farms, typically own about 2-5.0 ha of farmland and have more sources of income than the poor farmers. Corn production as a source of income provides an estimated 48-65% of this farmer group’s total household income, and non-farm activities provide about 6-14% of their total income. Typical non-farm income-earning activities for these farmers include buy and sell enterprises, driving public vehicles for hire, working in factories or stores in nearby cities, and working as construction laborers within or outside the community.

Philippine corn farmers in the rich farmer group tend to have smaller households, and larger farms (at least 5.0 ha), with typically more than one kind of crop grown. These rich corn farmers tend to be less economically dependent on corn production alone, which provides only about 29-56% of their household income. Of the three wealth categories, the rich Philippine corn farmers characteristically receive the highest proportion of their incomes (4-22%) from non-agricultural enterprises. These rich corn farmers or members of their family may have skills or education that allows them to hold white-collar jobs in bigger cities like Metro Manila, or to work overseas and send remittances home. Of the three farm categories, poor farmers make up the bulk of the corn farming population in the Philippines.

To augment corn production income, corn farmers in the Philippines also commonly raise livestock and poultry (i.e., smaller scale, “backyard” production). The most common animals raised by farmers in most corn-producing regions are swine and poultry, with market prices ranging from PhP60-75 (US$1.20-1.50)/kg or PhP67-100 (US$1.34-2.00)/head of swine and PhP37-70 (US$0.74-1.40)/kg of poultry. Local water buffalo (e.g., the carabao) and cattle on average sells for PhP7,500-18,000 (US$150.00-360.00)/head, while goats sold for PhP550-1,000(US$11-20.00)/head. These animals are usually sold when cash is much needed, for example, at the start of the school year if the farm households have children. Animals are also slaughtered for home consumption when there are special occasions.

2.5. Institutional Context and Agricultural Policies

2.5.1. Agricultural Extension Support and Government Subsidies

Government extension services provided directly through the Philippine Department of Agriculture (DA) have historically played an important role in providing technical information to corn producers in the major growing regions. DA agricultural technicians regularly conduct farmers' field schools (FFS) and training sessions, which provide farmers with updated technology and modern practices for corn production. Neighbors and other farmers within the community often share knowledge, and are regarded as valuable sources of information (especially after being trained through DA sources). However, concerns have been expressed about the need for DA agricultural technicians to be better trained in order to address specific corn production problems. Sometimes corn farmers comment that the inability of DA extension services to provide sufficient and updated information on agricultural technologies contributes to poor farm productivity.

Even though the DA have historically provided important government extension services to corn growers in the Philippines, the 1992 Local Government Code also allowed local government units (LGUs) to provide agricultural extension services through Municipal Agricultural Offices (MAOs). These offices are largely independent of the Philippine DA, and, as such, there is wide variation in the quality and effectiveness of extension services from these MAOs. In the Philippines, MAOs typically have limited human and financial resources, in order to bring sufficient and timely extension services to all barangays, and corn farmers have reported insufficient agricultural extension assistance from them.

Aside from DA and municipal sources of extension information, corn farmers in the Philippines also take advantage of other sources of corn farming information. Seed company field technicians also provide technical production information to corn farmers, but it is generally limited to the products they are selling. Several help organizations exist in major corn-producing regions, including: farmers' associations, cooperatives, and non-government organizations (NGOs). These groups provide technical, financial, or livelihood assistance to their members, in the form of livestock dissemination programs, small handiwork business assistance, and help in establishing small consumer (called "sari-sari") stores. Barangay or neighborhood officials, as well as women's, youth, and church organizations are also active in providing livelihood, leadership, and religious programs and seminars in corn producing communities.

There is typically limited extension support provided by local agricultural state universities or colleges (SUCs) near major corn-producing areas. In addition, international agricultural research centers (IARCs) focusing on corn production have historically not played a significant role in terms of extension support in the country.

Approximately 17% corn farmers in the major corn producing regions receive some form of subsidy from the government (PSA 2011). The most common subsidy received by corn farmers are through fertilizer subsidies. Other subsidies received by corn farmers in the Philippines are typically funds for obtaining irrigation services, drying facilities, and/or more education and training.

2.5.2. Borrowing and Credit Situation

As alluded to in previous sections above (e.g., the Material Inputs section), there is evidence that a large proportion of corn farmers in the Philippines lack sufficient capital for their farm operations (Gerpacio et al. 2004). These cash constrained corn farmers usually borrow from private trader-financiers on a charge-to-crop scheme, with a 10-20% interest rate. The private trader-financiers typically sell agricultural input products to the cash-constrained corn farmers, but at higher than market value. These trader-financiers then later buy back the harvests at lower than market value. In this lending scheme, the loans for agricultural inputs, as well as interest due for one cropping season, are deducted from the total value of the harvest that is in turn sold to the lender. Though this system seemed unfair and costly, the farmers think that going to the private trader-financiers is more convenient than going to formal credit institutions (like rural banks) for three reasons: (1) private loans do not require collateral, (2) the trader-financiers are always accessible, and (3) inputs were readily available. A number of corn farmers also state that they continue to use the services of private trader-financiers because income from a harvest is usually insufficient to pay for loans taken during the previous cropping season.

Nationally, only about 10% of corn farmers do not use the trader-financiers. About 8% of those farmers who do not use trader-financiers obtain credit from cooperatives, and only 2% had enough capital themselves. While formal credit programs and facilities were available from some government and private banks, corn farmers in the Philippines seldom used these sources because they found the paper work too tedious and the requirements (especially collateral) too strict. Farmers also noted that financial institutions only extend agricultural loans to farmer associations, not to individual farmers.

2.5.3. Road Infrastructure and Markets

The road networks in major corn producing provinces nationwide are typically accessible by all kinds of land transportation. Most of these corn producing provinces usually have graded and gravel roads that can be used throughout the year (even though most corn production is in rural areas). Some “interior” corn-producing villages (i.e., deeper in the upper plains for example), however, are not accessible to motor vehicles, especially during the rainy season. Farmers in these villages use animal drawn carts to haul their products to the nearest market.

Corn farmers in the Philippines typically sell their grain and other farm products either directly in public markets (i.e., primary markets in nearby municipalities or secondary markets in major cities or provincial capitals) or to the private traders who come to the farmers’ villages. In general, self-financed corn producers in the Philippines sell their grain in farther-off secondary markets, where prices are often high. Maize farmers with loans from trader-financiers have to sell their grain to these trader-financiers despite the low prices they often get. The trader-financiers come to the villages during harvest and haul the grain in volume. Trucking services (transportation costs) may be charged to the farmers, shouldered by the traders, or shared by both parties. Sometimes, farmers sell their production to feed millers in nearby areas (if possible). Farmers consider feed millers good market outlets because grain may fetch higher than market prices, and some feed mills do not have very strict grain quality standards.

2.6. GM Corn Adoption and Impacts in the Philippines

2.6.1. Evolution and History of Adoption and Use

The Philippines has traditionally been one of the leaders in agricultural technologies in South East Asia, dating back to the 70's with the introduction of high-yielding rice varieties. This position has been supported by educational facilities and institutions in the country, such as the University of the Philippines Los Banos, which have led the way in agricultural technology research in the region. Part of the motivation for research in these technologies is the recognition of the potential for these technologies to bolster rural incomes, contribute to agricultural growth and promote food security in the country. In 1980, the National Institutes of Biotechnology and Applied Microbiology (BIOTECH) was instituted in the University of the Philippines Los Banos and since then other such institutes were formed in the UP system. All of which has allowed information dissemination and the integration of this information into policies in the country.

While biotech research was being conducted in the Philippines in the 90's, it wasn't until 2003 that the first GMO product, GMO yellow corn, was introduced commercially in the Philippines. Food security and the need to reduce the import bill for yellow corn (which had averaged a quarter million tons annually prior to introduction) were among the major reasons for the move. The Asian corn borer, seen as a significant pest in the Philippines, can contribute to significant losses. Losses average about 40% in pest years and as much as 80% in particularly severe pest years (Nafus and Schreiner 1991) with importing often having to make up for these shortfalls. Bt yellow corn was therefore a natural target for policy makers in the Philippines.

Support for the adoption of GM crops has been primarily pioneered by information sharing from private seed companies. In some areas, farmers reported being exposed to demonstration farms, which were farms selected by seed companies to grow crops and show nearby farmers the benefits of the GM crops compared to the standard hybrids (Navarro and Hautea 2014). Farmers also reported being exposed to information about GM crops from farm cooperative membership and traders. Some of the reasons cited by farmers for choosing to adopt were the protection from pests, increased yield and income (for some), reduced effort and the ability to spend more time with other crops. Navarro and Hautea 2014 also reported farmers as pointing to the crops providing an intangible sense of "peace of mind" from planting these crops knowing that major pests would not reduce their harvest.

2.6.2. Economic Impact Studies of GM Corn in the Philippines: A Brief Review

The two varieties studied in this dissertation and often cited in the literature are the single trait Bt variety and a stacked Bt/HT variety. The Bt variety derives its name from the *Bacillus thuringensis* bacterium. This bacterium produces a toxin that is effective against lepidopteran pests, which includes the European Corn Borer (ECB) and the Asian Corn Borer (ACB). The gene that allows the bacterium to produce this toxin is transferred which confers resistance of these specific pests to the modified corn variety. The stacked Bt/HT, in addition to the Bt gene, also contains a gene that confers it resistance to the herbicide glyphosate (HT here is an acronym for herbicide tolerant). Glyphosate is the primary component of the herbicide Round-Up which is produced and marketed by Monsanto.

For the single trait Bt variety, introduced for commercial use in 2003 in the Philippines, the most significant benefit often reported is increased yield (Mutuc et al. 2012; J. M. J. Yorobe and Quicoy 2006; Mutuc, Rejesus and Yorobe 2011). This increased yield stems primarily from damage abatement, rather than from improvements in seed germ quality, since farmers in the Philippines tend to underutilize insecticides despite the damages of the Asian Corn Borer. On average, Bt corn yield gains have been found to be around 30-40% above traditional varieties nationally (J. M. J. Yorobe and Quicoy 2006; M Qaim 2009b; Qaim and Zilberman 2003). These yield gains come at a cost though, as Bt seeds can be as much as four times the price of traditional varieties and three time the price of hybrid seeds. However, farmers who adopted the varieties said that this increased cost was offset by reduced costs in pesticide application and labor time (Navarro and Hautea 2014).

The stacked Bt/HT variety, introduced for commercial use in the Philippines in 2006, adds a second trait for tolerance to the herbicide glyphosate. This corn variety therefore has both Asian Corn Borer resistance and offers farmers the ability to better control weeds by allowing greater herbicide use. Since its introduction, adoption of the stacked variety has outpaced the single trait Bt variety. Adoption of the single trait Bt corn had fallen to less than 10% of corn acreage by 2011 and by 2014 had practically been replaced by the stacked and other GM corn varieties (Aldemita, Villena and James 2015). Farmers cited reduced cost of inputs and ease of pest management as some of the reasons for the dramatic shift. Weeding is a particularly costly, time consuming and labor intensive task in the Philippines. Farmers reported experiencing significant input cost reductions when planting the stacked variety, particularly related to reduced weeding costs (Aldemita et al. 2015). Hence, similar to the case of Bt corn, farmers find that despite the higher cost of acquiring seeds for the stacked variety (up to 1.5 times the price of Bt variety and three times the cost of hybrids in the dataset used) the other benefits of the variety make it an economical choice.

Expenses for corn farmers varied by crop variety and farm location. Fertilizer and labor were the biggest expenses for farmers planting yellow corn typically averaging about 6,600 and 5,800 PHP respectively (PSA 2011). For GM corn farmers, those located in the uplands reported fertilizer as the most significant cost and seeds being their second highest cost. Labor came in third and was 18% of total costs of corn production. However, for farms in the uplands (more similar to farms represented in the sample for this study) labor costs were the highest expenditure category by a significant margin (46% of total costs) with fertilizer coming in second and seed costs falling third in line (Navarro and Hautea 2014)[6].

2.7. Description of the Data and Sampled Farms

The previous sections discussed the characteristics of farmers at the national level. In this section, we focus on the farmers surveyed in the data used in this dissertation. The survey was intended to present researchers and others with an understanding of GM corn use among commercial farmers in the Philippines. As most commercial farms have already switched from the traditional variety of corn in the Philippines, the baseline variety used in this sample was the hybrid variety; farmers still using traditional varieties were excluded from the sample. The discussion will proceed by first describing the data collection process,

[6] Costs were reported from a representative farm in both the upland and lowland regions from the Navarro and Hautea (2014) report.

including the location and varieties of choice of surveyed farmers. Then we will discuss the characteristics of farms in our sample with a view of comparing them to the previous discussion of farm characteristics nationally.

2.7.1. Sampling Methodology

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 represents a panel where 278 of the farmers surveyed in the 2007/2008 cycle were located, and data were also collected from them for the 2010/2011 cropping cycle. Data collected in the two survey years included information on their corn farming systems and environment, inputs and outputs, costs and revenues, marketing environment, and other factors related to Bt/HT corn cultivation (i.e., subjective perceptions about the technology). Actual data collection was implemented through face-to-face interviews using pre-tested questionnaires.

The survey was confined to the provinces of Isabela and South Cotabato, which are both major corn-producing areas with historically high levels of Bt adoption. Seventeen top corn producing barangays (i.e., the smallest political unit in the Philippines) from four towns were then purposely selected based on density of corn production. Using the list of corn farmers provided by the head of each barangay, 467 farmers were randomly selected to be included in the 2007/2008 survey round. Of the farmers surveyed in this round, 212 farmers used the hybrid variety and 254 used the Bt variety. Of the 467 farmers originally in the 2007/2008 sample, 278 were still planting corn in 2010/2011 crop year and these producers were interviewed a second time.

In the 2007/2008 crop year, the sample only included farmers who either adopted a hybrid variety or a single-trait Bt variety (i.e., the one that only has insect resistance, and no herbicide tolerance). The stacked variety that has both the insect resistance and herbicide tolerance traits was not yet widely promoted at that time and no producer in the 2007/2008 data set adopted the stacked variety (although already approved for release in 2006). In the 2010/2011 crop year, with the widespread promotion of the stacked variety between 2008 and 2010, there were now three kinds of farmers in the sample: (1) those who used hybrid varieties, (2) those who used the single-trait variety, and (3) those who used the stacked variety. Therefore, some of the hybrid farmers in 2007/2008 either continued to be hybrid producers in 2010/2011, or they switched to the single-trait Bt variety or the stacked variety. On the other hand, some of the original single-trait Bt adopters in the 2007/2008 survey data either continued to be a single-trait Bt user or switched to the stacked variety. Table 2.1 summarizes farmers by variety use in each year.

2.7.2. Surveyed Farm vs National Farm Characteristics

The primary purpose of this section is to highlight the national representativeness of the farmers in the sample and show some features pertinent to the rest of the dissertation. This will include the off-farm labor characteristics of the farmers in the sample and a discussion of plots other than the main plot[7]. In general, the farmers in the sample are similar with respect to some primary characteristics to commercial farmers in the national survey. In 2007 the average commercial farm in the sample planted 1.16 hectares to yellow corn while

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[7] Some farmers in the sample had multiple farm plots. Inputs, labor time etc. though were only observed for the main plots. This discussion will serve to answer the question is what remains unaccounted for in the following analyses.

in 2011 this number grew to 1.32 hectares. The Philippine Statistical Authority reported in 2009 that the average area under corn on commercial farms was 1.27 hectares. The average number of years of education reported in the sample is ~7 years, equivalent to a primary school level of education[8]. In the national sample, the average farmer spent ~ years in school, also equivalent to a primary school level of education. In both the national and the current sample, approximately 90% of the farm operators were male. However, the sample used here is slightly skewed towards farm owners and younger farmers, with the national sample showing no greater than 65% farm ownership and a mean age of 51 years for the farm operator. The sample used in this dissertation showed average farm ownership being ~ 77% and the average farmer age to be ~ 46 years in 2011[9].

Table 2.2 to Table 2.4 describe characteristics of farm operators by their decision to work off the farm. In general, the information presented mirrors the discussion presented at the national level well. Access to off-farm employment is highly related to years of schooling by the farm operator as reported in Gerpacio (2004). Table 2.2 shows that poorer farmers tended not to have off-farm employment, while the converse was true for wealthier (higher income) farmers. Table 2.2 shows that in 2011 the typical farmer with employment off the farm had approximately 8 years of schooling, while a farmer without off-farm employment only had about 6.7 years of schooling.

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[8] Primary school spans the first 1-6 years of education. An individual receives a high school diploma after 10 years of education.

[9] The national sample included the age and land ownership of yellow corn and white corn farmers planting both traditional and hybrid varieties. The sample used for this study contained only yellow corn farmers using, hybrid or GM varieties but did not contain farmers using the traditional variety.

The tables not only show the value of education for off-farm purposes, they also show the value of education on the farm as well. Table 2.4 compares farmers whose off-farm employment status remained unchanged across the two sample years. It shows that farmers who had off-farm employment not only had higher household incomes, but that this higher income is not only driven by additional off-farm sources of income, but by increased on-farm productivity as well. Table 2.4 shows that farmers with off-farm employment had yields that were ~1.5 times greater than farmers who never worked off the farm. This is suggestive of the returns to education in the Philippines and gives some rationale for the CIMMYT report stating the strong desire by farmers to educate their children and using farm income as a means of achieving this goal.

Table 2.5 and Table 2.6 show the breakdown of farms with multiple plots. In general, the main plot and input usage for the main plot was observed in the data, but only the crop variety and area of other plots were recorded for additional plots. Table 2.5 shows the number of farms by area and year with at least one additional plot and the number of farmers who planted a different crop on those additional plots. In general, a minority of farms had at least one additional plot of land (~20% of farms in 2007 and ~ 30% in 2011). In addition to that, only 7 farmers in 2007 planted a different crop variety on at least one of the additional plot than was planted to the main plot. No farmers mixed varieties in 2011. This says that the main plot of the sampled farms was representative of the corn farming practices of these farmers. There was little mixing or ‘experimenting’ with varieties done by the farmers according to the information presented in Table 2.5. Table 2.6 shows the proportion of corn land that was dedicated to a second plot in the sample. It shows that across the two years

~20% of land was on a plot of land other than the main plot (17% in 2007 and 21% in 2011). While this is a small proportion of land, it is perhaps not negligible. For spillover calculations in Chapter 4 care should be taken to consider this fact in interpreting results as estimates are based on land from the main plot only.

2.8. Conclusions

The discussion presented above serves to provide background on the institutions and context from which the data used for Chapters 3 and 4 of the dissertation were taken. Chapter 3 investigates the effect that adoption of two specific GM yellow corn crop varieties (Bt which gives Asian corn borer resistance and the stacked variety which has both pest resistance and herbicide tolerance) have on farm labor time allocation of in the Philippines. Chapter 4 investigates the effect that adopting these two GM crops can have on the incentive of other farmers to adopt similar varieties, through a public good mechanism. The public good here is pest damage abatement provision. Important for interpreting results produced in these two studies is understanding the behavior of farmers in the Philippines and most importantly, if assumptions made are likely to hold in the environment in which they operate.

In Chapter 3 where we look at labor time on and off the farm, it is important to understand the incentives to use updated crop varieties, the goal of farming (for family use or for commercial sale), government support, attitudes towards new technologies and access to amenities such as the new technologies in question, off farm employment and farm laborers. The preceding discussion shows that farmers' incentives to work (on or off the farm), in addition to income and consumption, includes a desire to educate their children. The on-farm work incentive is particularly important for poorer farmers who, due to having typically lower educational attainment, had lower access to off-farm work opportunities. This suggests that poor farmers in particular can use these incentives to exploit on-farm gains should they exist.

In exploring farmers' rationale for adopting GM technologies, some of the reasons farmers gave included the ease of crop management it provided, labor savings, yield protection, yield improvement, corporate promotion and farmer information sharing. These findings show that the reasons for adopting these varieties are numerous and the incentives complex. However, importantly, the aspects investigated in Chapter 3 and 4 (pest management, risk of crop loss and yield enhancement) play a role.

Off-farm opportunities were found to be available to some farmers but less so for others. Education significantly determines both farm wealth level and access to these jobs off the of the farm. However, the discussion also shows that many farmers have access to income smoothing alternatives to corn farming as many farmers also produced livestock, vegetables and other crops besides corn, and had opportunities to open Sari Sari stores through government assistance. These alternative sources of income were found to adjust income through the year when expenditures were not smooth such and suddenly increased, such as the beginning of the school year, to pay for related expenses.

Important for Chapter 4 which deals with the effect of area level adoption on individual adoption decisions, we discuss overall adoption patterns. The discussion here suggests that adoption of GM crops in the Philippines is non-negligible in terms of total farm land dedicated to these crops. Corn, being the second most important crop in the Philippines, covers a significant proportion of farmland and many yellow corn farmers have turned to using GM crops. Also, not uncommon is for some farmers who traditionally have grown white corn to switch to growing yellow corn, often deciding to grow GM varieties as well. This suggests that the adoption patterns noticed in the data can easily be generalized to other commercial yellow corn producing areas. This of course is significant since the effect estimated in Chapter 4 largely depends on the total area dedicated to the GM crops and the effect increases as more area is farmed with the variety.

The areas represented in the data for this study are those in the provinces of Isabela and South Cotabato. South Cotabato is located in the island group of Mindanao in the south (Figure 2.1) of the Philippines. Isabela is located in the north of the Philippines in the island group of Luzon where the capital of Manila is also located. Isabela and South Cotabato are among the highest yellow corn producing areas in the Philippines. However, of these high producing areas, Isabela and Mindanao represent two extremes of the commercial yellow corn producing areas. Isabela, being on the main island group, has high access to primary markets and yellow corn farmers in this area are among some of the highest yellow corn producers in the country. On the other hand, Mindanao due to factors such as weather, soil fertility and market access, are traditionally on the lower end of production (among commercial farmers, who on average, will typically still produce above mean yield at the national level). These two areas therefore represent the broad spectrum of commercial yellow corn producers in the Philippines and is representative of this population. Inferences from this sample can therefore give insight on this population of commercial yellow corn producers.

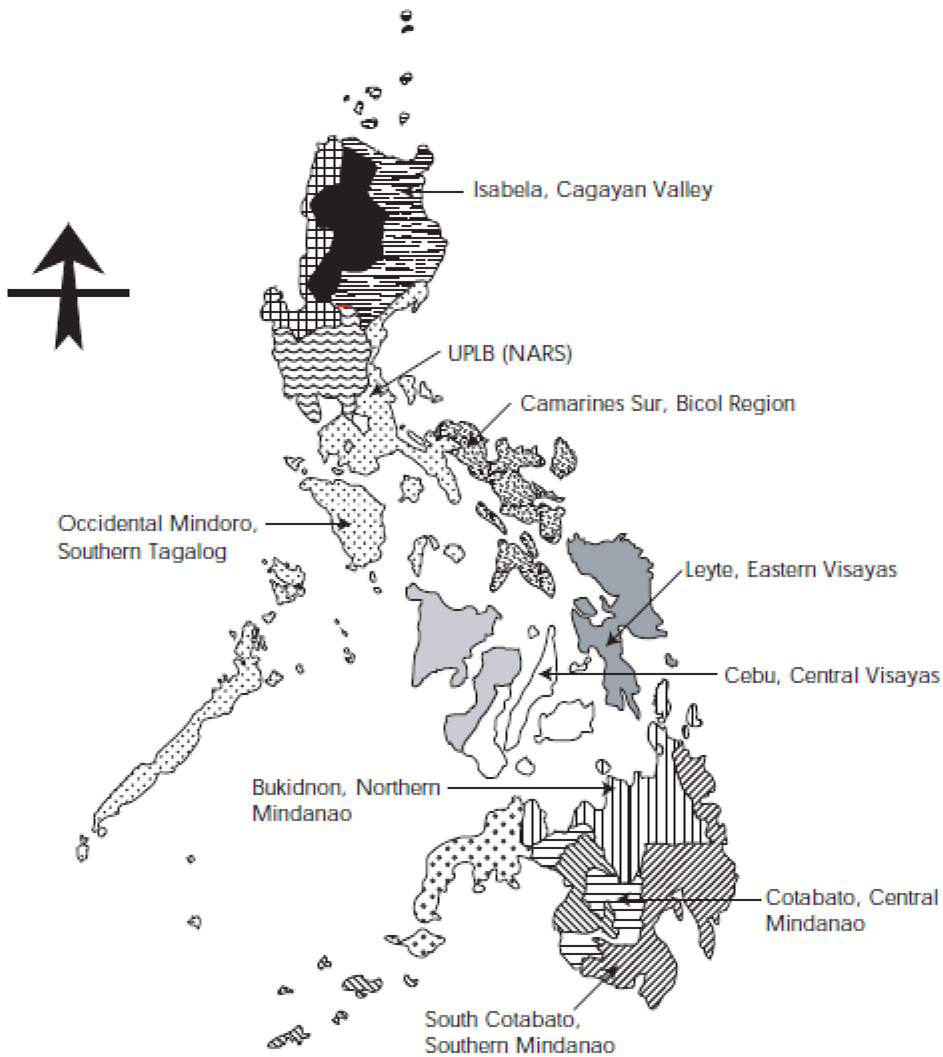

Figure 2.1. Map of the Philippines
Image borrowed from the Gerpacio et al. 2004 CIMMYT report “Maize in the Philippines: Production Systems, Constraints and Research Priorities.”

Table 2.1. Surveyed Farms by Crop Variety Choice

	2007		2011	
	Mindanao	Isabela	Mindanao	Isabela
Hybrid	120	93	31	2
Bt	73	181	14	9
Stacked	-	-	40	182
N	193	274	85	193

Table 2.2. Farmer Traits by Decision to Work Off the Farm in Each Sample Year

	Not Employed Off-Farm 2007[1]	Employed Off-Farm 2007	Not Employed Off-Farm 2011	Employed Off-Farm 2011
Operator Age	43.93	40.34	46.82	42.75
	(11.96)	(10.20)	(11.59)	(10.08)
Proportion Male	0.90	0.91	0.87	0.95
	(0.302)	(0.286)	(0.336)	(0.216)
Years of Schooling	6.96	7.78	6.67	8.02
	(2.883)	(3.223)	(2.526)	(3.470)
Household Income[2]	6416.44	6034.64	5822.97	8621.53
	(9330.7)	(4617.8)	(6316.2)	(9794.4)
Farm Size (Ha)	1.42	1.36	1.30	1.59
	(0.822)	(0.829)	(0.995)	(1.261)
Main Plot Size (Ha)	1.07	0.82	1.00	1.22
	(0.613)	(0.466)	(0.887)	(1.055)
Yield (Kg/Ha)	4183.66	4864.12	6027.99	6437.09
	(1667.5)	(1923.5)	(3438.0)	(6265.4)
Hybrid Users	0.44	0.39	0.06	0.16
	(0.497)	(0.491)	(0.235)	(0.364)
Bt Users	0.56	0.61	0.05	0.14
	(0.497)	(0.491)	(0.208)	(0.344)
Stacked Users	0.00	0.00	0.90	0.71
	(0)	(0)	(0.305)	(0.457)
N	179	79	155	103

Notes: [1]Eployment refers to being employed off the farm. [2]USD-PPP Adjusted.
Standard deviations in parentheses

Table 2.3. Farmer Traits by Decision to Switch Off-Farm Employment[1]

	Employed Off Farm in 2007 Only[1]	Employed Off Farm in 2011 Only
Operator Age	44.32	43.80
	(9.883)	(10.36)
Proportion Male	0.84	0.92
	(0.370)	(0.281)
Years of Schooling	6.49	7.44
	(2.955)	(3.706)
Household Income[2]	4637.63	8827.80
	(3612.1)	(11575.9)
Farm Size (Ha)	1.21	1.80
	(0.768)	(1.417)
Main Plot Size (Ha)	0.85	1.35
	(0.543)	(1.164)
Yield (Kg/Ha)	5492.85	5534.82
	(2333.0)	(2888.0)
Hybrid Users	0.05	0.24
	(0.211)	(0.429)
Bt Users	0.00	0.15
	(0)	(0.363)
Stacked Users	0.95	0.61
	(0.211)	(0.492)
N	44	59

Notes: [1]Table shows the 2011 characteristics of all farmers. [2]USD-PPP Adjusted.
Standard deviations in parentheses

Table 2.4. Traits of Farmers Always and Never Having Off-Farm Employment

	Never Employed Off-Farm		Always Employed Off-Farm	
	2007 Characteristics	2011 Characteristics	2007 Characteristics	2011 Characteristics
Operator Age	45.46	47.75	38.91	41.64
	(12.91)	(12.14)	(9.714)	(9.740)
Proportion Male	0.89	0.89	0.98	0.98
	(0.313)	(0.313)	(0.149)	(0.149)
Years of Schooling	6.69	6.69	8.86	8.86
	(2.326)	(2.326)	(2.962)	(2.962)
Household Income[1]	5324.36	6245.23	7134.36	8415.71
	(5433.5)	(7083.1)	(5475.5)	(6750.0)
Farm Size (Ha)	1.29	1.33	1.37	1.33
	(0.808)	(1.077)	(0.847)	(0.953)
Main Plot Size (Ha)	0.94	1.06	0.86	1.06
	(0.539)	(0.990)	(0.487)	(0.864)
Yield (Kg/Ha)	4241.05	6292.00	4999.88	7488.87
	(1612.6)	(3753.6)	(1734.5)	(8864.2)
Hybrid Users	0.40	0.05	0.36	0.07
	(0.492)	(0.228)	(0.484)	(0.252)
Bt Users	0.60	0.06	0.64	0.11
	(0.492)	(0.245)	(0.484)	(0.318)
Stacked Users	0.00	0.88	0.00	0.82
	(0.00)	(0.324)	(0.00)	(0.387)
N	110	110	45	45

Notes: [1]USD-PPP Adjusted. Standard deviations in parentheses

Table 2.5. Distribution of Farms with at Least Two Farm Plots

	2007			2011		
	Mindanao	Isabela	Totals	Mindanao	Isabela	Totals
No Second Plot	62	139	201	65	126	191
Second Plot	3	51	54	0	64	64
Different Crop on Second Plot	0	7	7	0	0	0
N	65	190	255	65	190	255

Table 2.6. Proportion of Land not on Main Plot

	2007	2011	Overall
Proportion of Land	0.17	0.21	0.19
N	255	255	255

CHAPTER 3

Labor Savings and Time Allocation Shifts from Pesticidal GM Corn Adoption in the Philippines

3.1. Introduction

Much research has been conducted on the primary impacts (effects on the farm, see: Mutuc, Rejesus, and Yorobe 2013; Qaim et al. 2006; Mutuc, Rejesus, and Yorobe 2011; Sanglestsawai, Rejesus, and Yorobe 2014; Fernandez-cornejo and Li 2005) and the secondary impacts (effects off the farm, see: Barrows et al. 2014; Kathage and Qaim 2012; Qaim, Martin and Zilberman 2013; Qaim 2009) [10] of GM crop adoption with various genetic traits. On-farm labor usage is one variable that has previously been investigated in the literature. However, past studies have typically treated the effect of GM crops on labor as static (i.e., its effect is similar in all environments). As such, GM crops are typically thought of as labor saving, given that they eliminate the need for specific pest control tasks – for example, weeding by hand being replaced with a less labor intensive herbicide spraying

[10] The overall literature generally indicates that farmers who adopt these Bt and HT crops tend to have higher *mean* yields relative to their non-adopting counterparts. Note, however, that various meta-analyses have concluded that mean yield (and yield distribution) effects of Bt and/or HT crops greatly vary by type of crop and/or by country (Matin Qaim 2009; Brookes and Barfoot 2008; Qaim, Pray and Zilberman 2008; Raybould and Quemada 2010; Finger et al. 2011). This highlights the importance of the empirical context of a particular study when assessing the effects of Bt and HT crop adoption on the yield distribution and other farmer decisions.

regime (Areal, Riesgo and Rodriguez-Cerezo, 2012) or reducing/eliminating the need for spraying pesticides to control specific pests.

However, some studies have already pointed out that feedback dynamics, that alter farmer incentives, are inherent in GM crop adoption systems. Aldana et al. (2012) show that input usage varies over time as farmers learn for themselves and from other farmers about the nature of GM crops and its effect on their farm. Brown, Connor, Rejesus and Yorobe in a working paper, argue that the adoption decisions of farmers can be affected by the adoption decisions of neighboring farms, since increased adoption rates can affect the degree of local pest pressure (Hutchison et al. 2010).

This study therefore examines the mechanisms by which adoption of Bt and/or HT corn varieties can affect on-farm labor use. Specifically, how expected changes in the yield distribution, due to GM crop adoption, influence on-farm labor use decisions. We empirically estimate how these kinds of GM crops impact specific within-season tasks (i.e., harrowing, planting, herbicide application, pesticide application, harvesting, etc.) for various labor types (i.e., operator, family, and hired labor). We posit that the labor effect of GM crops with Bt and/or HT traits is a combination of two effects: (1) a direct substitution effect between the Bt/HT seed and labor time/use, and (2) a complementary labor crowd-in effect due to the expected mean yield increase and yield variance reduction typically associated with Bt/HT technology. This latter effect influences the marginal product of labor used before harvest (for specific tasks) and during harvest. The direct substitution effect is expected to decrease on-farm labor use (i.e., specifically, for pest-management related tasks), while the complementary labor crowd-in effect is expected to increase on-farm labor use (i.e., particularly, for non-pest management related tasks like land preparation and harvest activities). The overall impact of the technology on on-farm labor use will therefore depend on the relative strengths of these competing effects.

With the use of a two-year panel data-set that contains information about farmers who adopt two kinds of GM varieties having differing impacts on the mean and variance of yield, we are able to estimate the on-farm labor responses to these two effects. We find that farms of the size represented in our sample (typically no larger than 2 hectares) are more sensitive to changes in risk exposure (e.g., changes in variance) than to changes in mean yield, particularly for labor in the pre-harvest phase. We also find that the overall positive labor crowd-in effects of GM crop adoption outweigh the direct labor-substitution effect in this context. This means that Philippine corn farmers who use GM crops tend to utilize more labor overall for on-farm activities than those who used non-GM hybrid varieties. We conclude that the overall impact of GM corn adoption on on-farm labor use will depend on the environment in which adoption occurred, the size of the farm, and the effect of the crop variety on the distribution of yield.

Recent work (e.g. Karlan et al. 2014) show that relaxing risk exposure on farmers can have noticeable impacts on input use decisions. Findings in the literature also support the conclusion that the effects of GM crops on the distribution of yield (i.e., such as GM effects on mean yields and yield risk / yield variability) [11] and their implied harvest time benefits can produce feedbacks on input use incentives even in the pre-harvest phase. For example,

[11] Several studies have already shown that Bt and HT technologies can statistically affect yield risk (i.e., second and higher moments of the yield distribution). See: Chavas and Shi 2015; Fernandez-Cornejo and Wechsler 2012; Finger et al. 2011; Hurley et al. 2004; Shankar et al. 2008; Shi, et al. 2013.

Emerick, de Janvry, and Sadoulet (2016) have shown that when producers adopt a "damage abating" [12] crop variety (i.e., a drought tolerant crop in their case), the yield protection conferred by the crop can also influence pre-harvest input-use decisions, such as the extent of fertilizer application. In the context of labor time, adoption of a risk-reducing or mean output increasing technology can enhance the productivity of some pre-harvest activities (like land preparation) in bad (high pest pressure) states of the world. As such, adoption of such technologies can provide incentives to increase (or crowd-in) labor time on some pre-harvest activities, where previously time spent on such tasks may have been lower.[13]

The results from studies that have directly and/or indirectly examined the on-farm labor use effects of GM adoption have also been mixed; lending support to the idea that context-specific feedbacks potentially play a role in explaining final outcomes. Studies using United States (US) data have shown that results depended on the GM crop being adopted and/or the income bracket of adopting farms (e.g. Gardner et al. 2009) or even the specific trait incorporated into crops (e.g. Fernandez-Cornejo et al. 2005).

Other research conducted outside of the US show similar patterns. Studies by for example Mutuc et al. (2012), Subramanian and Qaim (2009), Kouser et al. (2015) Gouse et al. (2009), Yorobe and Quicoy (2006) and Huesing and English (2004) have been valuable in

[12] A damage-abating input is one that decreases damage to crops in conditions that would normally result in yield loss. These have the effect of shrinking the left tail of the yield distribution. In contrast, yield-enhancing inputs increase yield in good conditions but offer little protection in bad conditions. Fertilizers often fall under this latter category.

[13] In other words, damage-abating technologies have the ability to improve the mean intertemporal marginal product of yield-enhancing inputs and tasks, thereby improving their performance even in conditions where productivity is expected to be low (in this context, high pest pressure periods). Thus, these damage-abating technologies can provide incentives to increase time spent applying yield-enhancing inputs and other pre-harvest tasks since time used during this period is less likely to suffer from a lower than expected pay-off at harvest time.

showing the context specific nature of GM crop adoption on labor use. They show that on-farm labor has at times increased, at other times decreased and may even have gender specific effects if tasks vary by gender; a common occurrence in agriculture in many developing countries. The variation in responses may at least in part, arise because of differences in yield effects of various GM crops/traits. These differences can generate unique combinations of feedbacks that affect labor incentives not only at harvest time, as has been previously investigated, but also in the pre-harvest phase.

3.2. Conceptual Framework

We present a theoretical framework of on-farm labor use under production uncertainty and with a damage-abating GM technology. This model is an extension of similar models presented by Binswanger (1981), Chavas and Holt (2011), Key, Roberts, and O'Donoghue (2006) and Mishra and Goodwin (1997) with the addition of labor saving feature of the adopted technology. In our context, the farmer chooses to adopt a GM crop variety that controls for pest damages and therefore replaces labor previously used for pest management related tasks. In addition, the crop variety may increase expected mean yields, reduce yield variance or both. We assume for simplicity that farmers have *a priori* expectations of the distribution of yield, conditional on crop choice. In the framework of Aldana et al. (2012), this is similar to assuming that sufficient time has passed since initial introduction of each variety for farmers to become knowledgeable about their effects on farm yield.[14] We will

[14] Data used for this study were collected four years after initial introduction of each GM variety. Results from our study assume that this time period is sufficient for farmers to gain accurate knowledge of the behavior of each GM variety on their farm.

therefore derive responses of a risk averse farmer facing either a change in expected mean yield and/or a change in the variance of yield. We also investigate differences in labor responses that occur before harvest, where uncertainty exists and at harvest time when yield uncertainty has been resolved (i.e., the outcome is known).

We begin by assuming risk averse farmers who work on and off the farm. The farmers make decisions about their labor time, as well as the use of other inputs. To avoid uncertainty during the harvest period related to things other than farm production, we assume that labor markets are well functioning, perfectly competitive, and wages are stable over time. In this way, farmers use off-farm labor as a means of income smoothing when the risk of farm losses increases.

Assume utility is a function of total income and leisure and that utility over these two variables is concave such that:

$$U = U(I, L) \qquad U_j' > 0, U_j'' < 0 \tag{1}$$

where $j = I, L$, and farm income is given by:

$$I = Y(A, (P-d), F, \theta) - C(Y, r) + wl + N, \qquad d \in [0,1] \tag{2}$$

and time is subject to the constraints:

$$T = F + l + d + L, \qquad F, l, d, L \geq 0 \tag{3}$$

For simplicity we normalize prices to 1. Y is a concave output (yield) function where $Y_i' > 0$, $Y_i'' < 0$ and i refers to all endogenous inputs to the production function, A is an exogenous measure of per hectare seed variety productivity. Hence, increases in A implies seed productivity is increasing, such that $\frac{\partial Y}{\partial A} > 0$. We assume that A is a function of the seed variety (V) the farm chooses. θ is a vector of farm and farm operator characteristics that affect farm production. N is non-earned income and asset holdings[15]. P represents the degree of pest pressure that the farm faces and is a function of the environmental conditions of the farm and the seed variety adopted by the farm. P affects farm productivity negatively such that $\frac{\partial Y}{\partial P} < 0$. d is labor dedicated to pest damage abatement (i.e., pest management related tasks). F is non-pest management related labor, l is off-farm labor time, w is off-farm wage, $C(Y,r)$ is the cost of producing Y units of corn. Hence households attempt to maximize $U = U(I,L)$ subject to the time and production constraints. Since utility is increasing in farm income, maximizing $U = U(I,\bar{L})$ is equivalent to maximizing:

$$I = Y\big(A,\tilde{P},F,\theta\big) - C(Y,r) + wl + N$$

s.t.

$$T = F + l + d$$

noting that $\tilde{P} = (P - d)$ is net pest pressure which depends on observed pests and the amount of labor applied to pest management. Additionally, $\frac{\partial Y}{\partial \tilde{P}} < 0$ since $\tilde{P}$ is a damage inducing input that reduces yields.

The first order conditions of this maximization problem are:

$$Y_F\left(1 - \frac{\partial C}{\partial Y}\right) = w \tag{4}$$

$$-Y_{\tilde{P}}\left(1 - \frac{\partial C}{\partial Y}\right) = w \tag{5}$$

[15] N represents the stock of accumulated wealth of the farm such as inheritances, the value of land and capital and financial assets.

Proposition 1: *Adoption of pest damage abating GM crop varieties will reduce labor time related to pest management.*

Total differentiating equation (5) with respect to d and P and solving for $\frac{\partial d}{\partial P}$ assuming optimality conditions yields:

$$\frac{\partial d}{\partial P} = 1 > 0 \tag{6}$$

Which says that labor time dedicated to pest management related tasks decreases as pesticidal crop varieties are adopted.

To introduce risk into our exposition we borrow the production function specified in Just and Pope (1977) which is represented as $Y = Y(x;\alpha) + h(z;\beta)\varepsilon$, where: $Y(x;\alpha)$ is the yield function specified earlier and $h(z;\beta)\varepsilon$ is a disturbance function that depends on factors that affect farm output variation, z and an exogenous disturbance factor ε. For simplicity, we assume that farm variance is directly proportional to output (yield variance is heteroskedastic and is a linear function of yield) and that the function $h(\cdot)\varepsilon$ can simply be represented by $h(\cdot)\varepsilon = Y(\cdot)\varepsilon$ where $Y(\cdot)$ is the yield function.[16] We will refer to ε as the intrinsic risk or intrinsic variation of farm production which is influenced in this context by factors such as the weather, soil conditions and characteristics of the seed variety chosen by the farm. Hence, we define the conditional expectation of farm yield and the conditional variance of farm yield as:

$$\mu = \mu(A(V), X, d, F) = \int Y \cdot f(\varepsilon | A(V), X, d, F) d\varepsilon \tag{7}$$

[16] Figure A.1 and Table A.10 show that the assumption of heteroskedastic yield holds in the sample used in the estimation procedure.

and

$$\sigma_Y^2 = \sigma_Y^2(V, X, d, F) = \int (Y - \mu)^2 \cdot f(\varepsilon | A(V), X, d, F) d\varepsilon \qquad (8)$$

where V is the crop variety that the farm adopts and σ_Y^2 is the heteroskedastic variance which depends on the yield level and σ^2, the variance of ε. Costs are normalized here to one and we assume that ε is the only source of randomness for farm income. These equations and equation (2) above imply that P, A, and ε are functions of the crop variety used by the farm, as well as farm input decisions. For this exposition, we assume that each variety affects the conditional expected mean yield through the scale parameter A and affects variance through ε. This implies that crop varieties affect E$[Y|A, d, F, X]$ and E$[(Y-\mu)^2|A, d, F, X, \varepsilon]$ through their effect on A and ε, such that the conditional mean and variance change value with inputs and labor time fixed. Unlike the deterministic case, utility maximization will depend not only on total income but also on the farm operator's risk tolerance. Hence, famers in this case maximize the expectation of utility (given the probability of farm income outcomes) subject to their time constraints.

To solve for the farm operator's expected utility let U^* be a second order Taylor approximation of U about the mean farm yield (with output prices normalized to 1), such that:

$$U^* = U + U'(Y - \mu) + \frac{1}{2}U''(Y - \mu)^2 \qquad (9)$$

Taking the expectation of U^* yields farmers' expected utility:

$$E[U^*] = U + \frac{1}{2}U''Y^2\sigma^2 \qquad (10)$$

Where U and U'' are taken at $\mu + wl + N$, the mean of farm income.[17] We also assume that off-farm labor wages at harvest time are constant over time. This implies that farmers harvest time labor decisions simply respond to observed yield (unknown at the time of planting) and hence farmers simply determine pre-harvest labor based on the known distribution of yield. The first order conditions for pre-harvest, on-farm labor decisions dedicated to pest management and non-pest management activities are given by maximizing equation (10). Dropping all third order terms yields:

$$U_I\mu_F + U_{II}\mu \cdot \mu_F\sigma^2 - U_I w = 0 \tag{11}$$

$$U_I\mu_d + U_{II}\mu \cdot \mu_d\sigma^2 - U_I w = 0 \tag{12}$$

$$U_I w - U_L = 0 \tag{13}$$

μ_d[18] is the response of mean yield to changes in damage abating labor time on the farm and μ_F is the response of mean yield to changes in farm labor dedicated to non-pest management related tasks.

Equation (11) is the equation of primary interest. Given that we are interested in farm behavior upon adoption of a damage abating technology that reduces pest pressure, we further assume that adoption of the pest resistant variety reduces pest pressure to zero. Thus, equation (12) yields the unique boundary solution of d = 0. At this point, assuming leisure is exogenously fixed allows us to focus exclusively on the effects of changes in the marginal

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[17] The Taylor series approximation was taken at the mean of farm yield and not total farm income since we assume stable off-farm markets and normalized output and input prices, hence farm yield is the only source of income variation on the farm.

[18] μ_i $i = F, d$ is taken as the net of marginal product and marginal costs with respect to d and F ($\frac{\partial\mu}{\partial i} - \frac{\partial C}{\partial \mu}$). The analysis that follows is valid as long as $\frac{\partial\mu}{\partial i} > \frac{\partial C}{\partial \mu}$. This assumption is innocuous since $\frac{\partial\mu}{\partial i} < \frac{\partial C}{\partial \mu}$ is, in general, not consistent with profit maximization.

product of farm time on farmer choices to work on the farm rather than non-labor activities.[19] We therefore substitute the use of U' in place of U_I and U_L since solving for on-farm labor time uniquely determines off-farm labor time as well given that leisure is fixed. Totally differentiating equation (11) with respect to A and solving for $\frac{\partial F}{\partial A}$ gives rise to Proposition 2.

Proposition 2*: An expected mean yield increase will increase labor time on non-pest management pre-harvest tasks if:*

$$\frac{\partial F}{\partial A} = \frac{-\left(\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}\right)}{S.O.C.} > 0 \tag{14}$$

Where $S.O.C.$ is the second order condition for a maximum and δ is a function of marginal products.

Proposition 2 implies that an expected increase in mean yield at the end of the cropping season will have an ambiguous effect on labor time allocation at the beginning of the cropping season. The effect will depend on the size of this increase and the risk tolerance of the farmer. This leads to Corollary 1.

Corollary 1: $\frac{\partial F}{\partial A}$ *is positive if:* $\mu_{FA} > \left|\left(\frac{U''}{U'}\right)\delta\sigma^2\right|$

Proposition 2 and Corollary 1 taken together say that the pre-harvest effect of an expected mean yield increase will depend on μ_{FA}, the size of the change of on farm marginal product, and $\left(\frac{U''}{U'}\right)\delta\sigma^2$ which can be interpreted as the farmer's sensitivity to risk. Hence, if farmers are very risk sensitive, an increase in farm productivity may reduce on-farm work, while

[19] The proofs of Propositions and Corollaries can be found in Appendix B. Appendix B discusses the implications of the fixed leisure assumption. The essential difference is that adjustments to on-farm labor arise exclusively from adjustments to from off-farm work time rather than from (or to) leisure time.

farmers who are less sensitive to risk would increase hours worked on the farm, taking advantage of the increased return to labor.

Corollary 1 implies that it's difficult to predict the behavior of farmers at the start of the cropping season in response to expected changes in mean yield at the end of the cropping season without making further assumptions about the risk preferences of farmers. Previous studies on the matter suggest that farmers exhibit behavior consistent with DARA preferences (for example Hennessy 1998; Binswanger 1981; Chavas and Holt 2011). This leads us to Corollary 2.

Corollary 2: *For farmers with DARA preferences,* $\frac{\partial F}{\partial A}$ *increases as farm wealth (N) increases, all else equal.*[20]

From our initial set-up, DARA preferences imply that $-\frac{U''}{U'}$ decreases as N, which measures farm wealth, increases. This implies that $\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}$ gets larger as wealth increases, all else equal. That is to say that on-farm labor more readily increases in response to increases in farm productivity on larger farms than on smaller ones.[21] Corollary 2 conforms to prior findings in the literature that suggest that farmers appear to exhibit DARA preferences and that Bt adoption (seen as a yield increasing variety) increases off-farm labor for smaller farms (for example Gardner et al. 2009).[22]

[20] Figure 3.1 illustrates Corollaries 2, 3 and 4.

[21] An implication from this is that in an unbiased regression of on farm labor on determinants of labor time, an interaction of a mean increasing farming input and farm wealth is expected to have a positive sign for labor tasks performed in the pre-harvest if farmers exhibit DARA preferences.

[22] If preferences are CARA, then the effect is independent of farm wealth. However, findings in the literature do not align well with farmers having CARA preferences.

The second component of yield that can also affect behavior other than the mean is the "riskiness" or variation of outcomes associated with that mean value. Farmers, when allocating labor hours and resources may not only consider the mean outcome, but also the chances of events outside of the mean outcome occurring. Therefore, we also consider deviations from mean or variance effects.

Proposition 3: *If farmers are risk averse, decreases in the variance (risk) of farm yields increase pre-harvest, non-pest management farm labor.*

$$\frac{\partial F}{\partial \sigma^2} = -\left(\frac{U''}{U'}\right) \cdot \frac{\mu \cdot \mu_F}{S.O.C.} \tag{15}$$

By totally differentiating equation (11) with respect to σ^2 and F and solving for $\frac{\partial F}{\partial \sigma^2}$ we get equation (15) which represents the effect of an exogenous change in intrinsic farm risk on on-farm labor from which proposition 3 follows.

Equation (15) is a negative value (the proof of which is in Appendix B) and suggests that farmers increase labor time on the farm in response to decreases in farm yield variability. Equation (15) also implies that the response to risk also depends on the risk preferences of farmers.

Corollary 3: *If farmer preferences are DARA* $\frac{\partial F}{\partial \sigma^2}$ *decreases as farm wealth (N) increases, all else equal.*

Corollary 3 implies that responsiveness to risk decreases as farm wealth increases.[23] This contrasts with Corollary 2 that implies responsiveness to mean yield increases with wealth. We can join these two predictions to give us Corollary 4.

Corollary 4: *For very small farms:* $\frac{\partial F}{\partial A} < \frac{\partial F}{\partial \sigma^2}$ *if farmers have DARA preferences*

Corollary 4 can be derived directly from implications in Corollaries 2 and 3. Figure 3.1 shows the expected behavior of on-farm work in response to both risk and mean yield changes for farmers with DARA preferences. Corollary 4 implies more that it appears. It produces a testable prediction that will be used in this study. It says that, in the pre-harvest phase, poorer farmers are expected to have a stronger on farm labor response to changes in yield risk than they would to similar changes in expected mean yield. It also says that these effects change in different directions as wealth changes for farmers who display DARA preferences.

To produce comparative statics for harvest time on-farm labor, we assume that at harvest time the farmer simply optimizes utility of time on the farm conditional on the revealed yield outcome and the marginal benefits of such on-farm labor time. Therefore, farmers simply solve the problem of a risk neutral farmer where the first order condition is:

$$U'\mu_F^* - U'w = 0 \tag{16}$$

or

$$\mu_F^* = w \tag{17}$$

[23] As with Corollary 2, Corollary 3 suggests testable implications of the response to changes in risk exposure in the pre-harvest phase. In this case, the sign of a coefficient on an interaction between a risk reducing farm input and farm wealth is expected to be negative for work done in the pre-harvest phase, if farmers exhibit DARA preferences.

where μ_i^* is the mean of realized yield conditional on first period input and labor choice and $\frac{\partial \mu_i^*}{\partial F} > 0$, $\frac{\partial \mu_i^*}{\partial A} > 0$. This assumption allows us to compare farmer responses in the pre-harvest and harvest phase of the cropping season.

Proposition 4: *Changes in expected mean yields produce larger changes in harvest labor than similar changes in the pre-harvest phase, in expected terms.*

$$\frac{\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}}{S.O.C.} < \frac{\mu_{FA}^*}{U'\mu_{FF}^*} \tag{18}$$

Totally differentiating equation (16) with respect to F and A and comparing the result to equation (14) gives equation (18) and proposition 4. Equation (18) implies that for an increase in expected mean yield, harvest time labor will increase by a greater amount than pre-harvest labor time. This also implies that the effect of a mean yield increase will induce behavioral responses in both the pre-harvest and harvest periods. Given that a change in the risk of yield does not affect mean outcomes at harvest time, this implies that changes in risk exposure are not expected to have an impact on mean labor input at harvest time. This yields Corollary 5.

Corollary 5: *A change in risk induces changes in the pre-harvest phase only.*[24]

This result follows from equation (17) which implies that $\frac{\partial \mu_F^*}{\partial \sigma^2} = 0$ and simply says that in the absence of a mean effect, mean labor input will be unaffected when the variance of yield changes. However, changes in pre-harvest labor and input mixes could change realized

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[24] This ignores how changes to input use in the pre-harvest phase feeds back in to outputs at harvest time which will have impacts on labor use at that time.

yield at harvest time and induce a labor change. This secondary response is not directly accounted for in the theory presented here[25]. We can now put these conclusions together to present a proposition that determines how labor time is expected to change if a variance or mean yield changing farm input is adopted.

Proposition 5: *A pest eliminating, labor saving technology that affects mean production and/or risk can induce a net increase in total on-farm labor.*

Using equation (13) combined with equations (14), (15) and (18), and the implication that $\frac{\partial d}{\partial V_P} < 0$, where V_p is the percentage adoption of pesticidal crop variety V, we can now show that for decreases in pest pressure accompanied by a decrease in risk or an increase in expected yield, total on-farm labor increases only if:

$$\sum_i \frac{\partial F_i}{\partial \sigma^2} + \sum_i \frac{\partial F_i}{\partial A} + \sum_j \frac{\partial d_j}{\partial V_p} > 0 \tag{19}$$

where i is all tasks related to non-pest management activities both at pre-harvest and harvest and k is all tasks related to pest management activities. Equation (19) implies that total pre-harvest on-farm labor will increase if the sum of effects of an expected mean yield increase and/or a variance decrease are sufficient to outweigh the total reduction in labor saved on pest management. Based on discussions so far, the extent of changes in non-pest management tasks will depend on factors that affect sensitivity to risk such as farm wealth,

[25] Since outcomes have been revealed, pre-harvest uncertainty does not directly affect harvest time labor. However, harvest labor is indirectly affected by pre-harvest uncertainty since it affects labor decisions in the pre-harvest phase which in turn affect harvest time labor. This also applies to the pure mean yield change equations. This implies that a decrease in risk exposure in the pre-harvest phase can produce observable increases in harvest time labor, particularly for risk averse farmers, if the increase in input use in the pre-harvest phase is sufficient to significantly increase yields at harvest time.

off-farm wage, individual risk preferences and availability of other risk mitigating instruments.

The framework above provides testable predictions to allow empirical investigation of the importance of changes in expected mean yield and yield risk (that GM crops can produce) on labor time decisions of adopting farmers. It shows that, in general, the effect of GM crops on farmers will depend on the risk preferences of farmers (which at least empirically can be affected by the extent to which farmers bear their own risks) and the effect of the GM crops on the distribution of yield.

3.3. Empirical Setting and Data Description

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 in the Philippines is typically grown 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 (Gerpacio et al. 2004; Mendoza and Rosegrant 1995).

The most destructive pest in the major corn producing regions of the Philippines is the Asian corn borer (ACB) (Morallo-Rejesus and Punzalan 2002). Prior to the widespread adoption of GM crops in the Philippines, 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. (2004) also report that corn farmers in major producing regions only typically 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 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 adoption, 2003, Bt corn were 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% equal to about 500,000 hectares. Since its introduction in 2006, adoption of the Bt/HT variety has steadily outpaced adoption of the single trait Bt variety. By 2012 GM corn coverage in the Philippines reached ~60% of all yellow corn planted. However, only 6% of this GM area was Bt. Apart from Monsanto, Pioneer Hi-Bred (since 2003) and Syngenta (since 2005) sell Bt/HT 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 represents a panel where 278 of the farmers surveyed in the 2007/2008 cycle were located, and data were also collected from them for the 2010/2011 cropping cycle. Data collected in the two survey years included information on their corn farming systems and environment, inputs and outputs, costs and revenues, marketing environment, and other factors related to Bt/HT corn cultivation (i.e., subjective perceptions about the technology). Actual data collection was implemented through face-to-face interviews using pre-tested questionnaires.

The survey was confined to the provinces of Isabela and South Cotabato, which are both major corn-producing areas with historically high levels of Bt adoption. Seventeen top corn producing barangays (i.e., the smallest political unit in the Philippines) from four towns were then purposely selected based on density of corn production. Using the list of corn farmers provided by the head of each barangay, 467 farmers were randomly selected to be included in the 2007/2008 survey round. Of the 467 farmers originally in the 2007/2008 sample, 278 were still planting corn in 2010/2011 crop year and these producers were interviewed a second time (which gives us an initial balanced panel data set of 556 observations)[26]. After dropping farmers with missing and inconsistent information a total of 510 observations remained for analysis. In 2007, 105 of these farmers planted hybrid corn and 150 planted Bt. In the second survey year, 17 planted hybrid, 22 planted singlet-trait Bt corn and 216 planted the stacked Bt/HT variety.[27]

In the 2007/2008 crop year, the sample only included farmers who either adopted a hybrid variety or a single-trait Bt variety (i.e., the one that only has insect resistance, and no

[26] The attrition of farmers here produces a possible bias in the sample. Weighted regressions were done to account for this. However, the results were similar to the main results which reduced the concern of attrition bias to the authors.

[27] While there are farmers that still use traditional varieties of yellow corn in the Philippines, the non-GM corn farmers in our data set are strictly hybrid corn users. There are no non-GM farmers that used traditional varieties in the data. This uniformity in the non-Bt group allows for a useful baseline to more meaningfully compare the performance difference between Bt/HT corn farmers relative to a more homogenous population of non-GM farmers (i.e. hybrid corn users only).

herbicide tolerance). The stacked variety that has both the insect resistance and herbicide tolerance traits was not yet widely promoted at that time and no producer in the 2007/2008 data set adopted the stacked variety (although already approved for release in 2006). In the 2010/2011 crop year, with the widespread promotion of the stacked variety between 2008 and 2010, there were now three kinds of farmers in the sample: (1) those who used hybrid varieties, (2) those who used the single-trait variety, and (3) those who used the stacked variety. Therefore, some of the hybrid farmers in 2007/2008 either continued to be hybrid producers in 2010/2011, or they switched to the single-trait Bt variety or the stacked variety. On the other hand, some of the original single-trait Bt adopters in the 2007/2008 survey data either continued to be a single-trait Bt user or switched to the stacked variety.

3.4. Estimation Strategy and Empirical Specification

In this study, we investigate the impact of adopting GM corn varieties with insect resistance and/or herbicide tolerance traits on the labor man-days worked on farms in the Philippines. We focus on the effect of GM crop adoption of three labor types – operator labor, family labor, and hired labor – as well as GM crop effects on an aggregate labor measure for "all types" (sum of operator, family, and hired labor) of labor.

We assume that total labor man-days worked on the farm (for all labor types) are determined according to the following empirical specification:

$$H_{it} = \beta_1 V_{it}^{Bt} + \beta_2 V_{it}^{St} + \beta_3 X_{it} + \beta_4 w_{it} + T_t + \alpha_i + \varepsilon_{it} \qquad (20)$$

where H_{it} signifies total man-days spent working on farm i in period t (for all labor types), V_{it}^{Bt} is a dummy variable =1 if the farmer adopted a single-trait Bt corn variety (=zero otherwise), V_{it}^{St} is a dummy variable =1 if the farmer adopted a stacked corn variety with both Bt and HT traits (=zero otherwise), X_{it} is a vector of observed farm/farmer characteristics, w_{it} is the individual-specific, equilibrium off-farm wage, T_t is a time trend/effect (in our case, a time dummy variable =1 if crop year = 2011 and zero, otherwise), α_i is a time-invariant individual-specific fixed effect, and ε_{it} is the disturbance term.

The variables of interest in the specification in (20), V_{it}^{Bt} and V_{it}^{St}, provide an estimate of the effect of GM crop choice on labor time used on the farm (e.g., choice of single-trait Bt or stacked variety; with hybrids as the omitted category). However, given that crop variety choice is not randomly assigned, there may be an inherent endogeneity problem due to the unobserved compound error $(\alpha_i + \varepsilon_{it})$ being correlated with the GM crop variety dummies. But if we assume that the main unobserved variable that drives the correlation between GM variety choice and the compound error is unobserved management ability (which is usually viewed as time-invariant), then we can reasonably say that this endogeneity problem can be accounted for by utilizing the panel nature of our data set. The individual-specific fixed effects α_i, can be estimated using individual dummy variables. Once the individual-specific effects are controlled for, a time trend/effect T_t is also included in (20) to account for unobserved time-varying secular trends.[28] We argue that including both the

[28] Village specific time trends are used in the estimation procedure.

individual-specific fixed effects and the time-trend together likely accounts for all possible unobservable variables that may cause endogeneity issues (i.e., and/or selection bias).[29]

Estimation of equation in (20) only applies to the aggregate hours worked for all labor types (i.e., aggregate hours worked for operator (H_{it}^{op}), hired (H_{it}^{hired}), and family (H_{it}^{fam}). Separate estimations of equations similar to (20) above can be used to estimate GM crop adoption effects on the three labor types (i.e., with H_{it}^{op}, H_{it}^{hired}, and H_{it}^{fam} as dependent variables in each run). However, estimating equation (20) separately for these three labor types implicitly assume that these labor allocation decisions are made independently of each other. In reality, it is likely that the hours of labor allocated for each labor type are correlated with each other (i.e., since all three labor allocation decisions are likely decided upon by all the members of the household) and this correlation needs to be accounted for in the estimation (i.e., since it will likely bias the standard errors if not). Therefore, a combined fixed effects and seemingly unrelated regression (SUR) approach (e.g., a fixed effects-SUR approach) is used to estimate the following system of farm labor type equations:[30]

$$H_{it}^{op} = \beta_1 V_{it}^{Bt} + \beta_2 V_{it}^{St} + \beta_3 X_{it} + \beta_4 w_{it} + T_t + \alpha_i + \varepsilon_{it}^{op} \qquad (21)$$

[29] One possible unobserved variable not included in the specification in equation (20) is time-varying on-farm wages (i.e., the price of labor). This may cause endogeneity issues in the sense that disturbance term ε_{it}, which in this case has the unobserved wages embedded in it, would likely be correlated with off-farm wages w_{it} (or even the variety dummies). However, if we assume that on-farm wage is partly a function of management ability and that on-farm wages for all farmers in the sample evolve over time at a somewhat similar rate, then one can argue that unobserved wages are adequately controlled for using both the individual-specific fixed effects and a time trend in the specification (as we do here).

[30] Table A.11 shows the results of the Breusch-Pagan test of independence of the three equations. The test rejects independence of the three equations with greater than 99% confidence.

$$H_{it}^{hired} = \beta_1 V_{it}^{Bt} + \beta_2 V_{it}^{St} + \beta_3 X_{it} + \beta_4 w_{it} + T_t + \alpha_i + \varepsilon_{it}^{hired} \tag{22}$$

$$H_{it}^{fam} = \beta_1 V_{it}^{Bt} + \beta_2 V_{it}^{St} + \beta_3 X_{it} + \beta_4 w_{it} + T_t + \alpha_i + \varepsilon_{it}^{fam}. \tag{23}$$

Given that the right-hand side variables are the same for equations (21) to (23), the estimated parameters in the combined “fixed effects-SUR” approach will be exactly the same as the equation-by-equation fixed effects estimation. However, standard errors will be more accurate using the combined “fixed effects-SUR” method because we account for the correlation across error terms. As pointed out in Bezlepkina, Lansink, and Oskam (2005), performing fixed effects within a SUR model can present issues. Therefore, we exploit the two-year panel nature of the data and note that estimating a first difference model is identical to a fixed effects model with a two-year panel. As such, we perform SUR estimations on the first differenced data to retrieve consistent estimates of the coefficients and standard errors. To maintain consistency, we also estimate the equation on the total man-days equation using first differencing.[31] As a robustness check, a model where standard errors are clustered at the village level and weighting to account for the potential of attrition bias were performed. The

[31] We also perform a three stage least squares instrumental variables estimation as a robustness check. The results are similar with the exception that the results present stricter conformance to the theoretical predictions of our model with weeding time decreasing and herbicide labor time increasing for stacked adopters. Harvest period labor time also has lower coefficient estimates at harvest time than those of Bt adopters. Instruments used are ones which are expected to influence the decision to adopt GM corn but are not themselves expected to be related to affect farm labor decisions, which were distance to the nearest seed source and an indicator variable of farm topography. As the results are not significantly different from the results reported for the straightforward first differenced results, the three-stage results are not reported in the main text and are used mainly to test whether our approach indeed eliminated the major sources of endogeneity, particularly in the pre-harvest period. The similarity of parameter estimates confirm that this is likely the case (results moved further in the direction predicted by the model which suggests that any endogeneity that remains likely produces conservative estimates of our variables of interest). The results are presented in Table A.6.

results were similar to the estimations procedures suggested above and are presented in Table A.12 - Table A.20

In summary, we estimate the effect of GM crop adoption on total labor hours used on the farm (the sum of all labor types) using a first differenced estimation of equation (20). The effect of GM crops on each labor type is estimated using SUR regression of equations (21) - (23), where the data is first differenced prior to estimation. In each case the effect on total hours worked on the farm, on pre-harvest labor (which includes land preparation and planting tasks), on chemical and pest management tasks (e.g. pesticide and herbicide application) and harvest time labor hours (e.g. shelling, bagging and transport) are investigated.

As shown in the equations above, our empirical specification for each labor use equation includes a vector of observed farm/farmer characteristics (X_{it}), and an individual-specific equilibrium off-farm wage (w_{it}). The actual independent variables included in the vector X_{it} for our estimating equation are included as controls of farm characteristics that can influence labor hours on the farm. Area planted and farm area are included as controls of baseline labor needs of the farm. Larger farms, planting more corn, will require greater labor time. Farm irrigation practices are included as this may be correlated with farm wealth. Farm topography is included to control for land quality and farming intensity (Gerpacio 2004) discusses the importance of terrain in determining agricultural choices in the Philippines). Household size controls for family labor availability. Farm ownership (an indicator for whether the farmer owns the farm or not) can proxy for the level of investment in the farm. Monthly income earned for non-farming activities for the farmer, as well as for the family, are proxies for off-farm wage and the opportunity cost of on-farm labor time.

3.5. Results and Discussion

3.5.1. Descriptive Statistics: Mean Labor Use across Labor Types and Production Activities

To get an initial perspective on the labor use of farmers adopting different GM corn varieties, descriptive statistics on labor allocation across labor-types (for each variety-survey year combination) are presented in Table 3.1. In addition, Table 3.2 provides descriptive statistics on the labor use across different farm activities (for each variety-survey year combination).[32] In general, data from the first year survey (2007) indicates that labor use tend to be higher for single-trait Bt adopters as compared to hybrid users (with the exception of family labor) (Table 3.1). In contrast, in the second survey year (2010) single-trait Bt and stacked Bt/HT trait adopters generally use less labor than hybrid corn producers (with the exception of the operator labor) (Table 3.1). Hence, based on the contrasting mean labor use values of GM adopters and non-adopters in the two survey years, it is difficult to ascertain whether single-trait Bt and/or stacked Bt/HT tend to increase or decrease overall labor use based solely on these mean values.

Table 3.2 presents statistics on the sum of time worked for all labor types (man-days) split out by tasks performed. It paints a similar picture to Table 3.1 while showing clear reduction in man days spent applying pesticides for Bt and Stacked adopters as well as a decrease in weeding man days for stacked adopters as expected. However, we also see a reduction in man days for land preparation and harvest man days for both Bt and stacked adopters. Table 3 reveals other trends which illuminate the need for regression estimations in

[32] Descriptive statistics of the remaining independent variables included in the empirical specification in equations 11-13 are presented in Table 3.3.

this context since Bt and stacked adopters tend to be on smaller farms and plant fewer hectares on average than their hybrid adopting peers. However, there is also greater variation in these characteristics for stacked and Bt farms. This shows that it is difficult to isolate the impact that GM adoption is having on labor man days simply from the means of the adopting populations and a more formal estimation procedure needs to be used.

3.5.2. Effects of GM Varieties on Total On-Farm Labor Use

In Table 3.4, we present the effects of single-trait Bt adoption and stacked trait Bt/HT adoption on total man-days spent on the farm (i.e., sum of labor time across all production activities) for each labor type (as well as for the sum of all labor types i.e., last row in Table 3.4).[33] On average, we find that farmers who adopt single-trait and stacked varieties of corn utilize more labor for their farm operations overall, relative to farmers who plant the hybrid variety. Single-trait Bt producers use about 12 man-days more than hybrid corn producers, while stacked variety producers allocate about 18 man-days more than hybrid corn producers (See last row in Table 3.4). But note that only the effect of the single-trait Bt variety is statistically significant at the 10% level (although the stacked variety effect on total labor use is marginally significant at the 12% level).

These estimates, using the interpretation of Proposition 5 in our theoretical model, suggest that the previously discussed labor crowd in effects were sufficient to outweigh the labor savings from adoption. That is, the positive complementary labor crowd-in effect on pre-harvest and harvest labor (i.e., due to the expected mean yield increase and risk reduction

[33] Note that, in Table 3.4, we only present the fixed effects and fixed effects-SUR parameter estimates that are associated with the single-trait Bt dummy and the stacked Bt/HT dummy in Table 3.4. The full specification results are presented in Table A.1 (for total labor use effects across all production activities).

from GM crops) outweighs the direct pest management labor saving effect. Gerpacio et al. (2004) reported that poorer farmers tended to be less educated than more wealthy farmers and were also less likely to work off the farm. This could also imply differences in off-farm opportunities and therefore differences in incentive to increase on-farm labor. Also, their study mentions that the culture in the Philippines and among farmers, is to educate their children in order for them to have more opportunities off of the farm in the future. This motivation may provide additional rationale behind to incentive to exploit productivity changes on the farm rather than use saved time for leisure, particularly for poorer farmers.

3.5.3. Effects of GM Varieties on Total On-Farm Labor Use by Production Activity

Based on our conceptual framework, it is also important to investigate the effect of GM crop adoption on total labor used for specific production tasks. We first examine this issue for all labor types (i.e., looking at the effect of GM adoption on the sum of operator, family, and hired labor time allocated for each task) and results are presented in Table 3.5. Several results are of note. First, consistent with Proposition 1 in our conceptual model, we find that GM crop adoption generally leads to a reduction in total labor used for pest management related activities. In the middle panel of Table 3.5, we see that the coefficients associated with weeding and pesticide application is negative (although only the labor use reduction for weeding is statistically significant). This implies that total labor used for these pest management related tasks tend to be smaller for farmers who adopt single-trait Bt and stacked Bt/HT varieties (as compared to hybrid users). This behavior reflects the direct substitution effect between the Bt/HT seed and labor time/use.

Second, we observe that the positive labor effects of GM crop adoption are mostly associated with non-pest management activities. In the top and bottom panel of Table 3.5, the coefficients associated with the single-trait Bt and stacked Bt/HT dummy variables generally have a positive sign for land preparation and (with some being statistically significant). This result is consistent with Propositions 2 and 3 in our conceptual framework, where we argue that the mean yield increasing effect and the variance reducing effect of GM crops are likely to increase labor used for non-pest management activities (especially for farmers with DARA preferences).

Third, the magnitudes of the positive labor effects for harvest activities tend to be larger than the magnitudes of the labor effects for non-harvest activities (i.e., comparing the magnitude of the parameter estimates in the bottom panel of Table 3.5 to the top panel). For example, the labor effect of stacked Bt/HT adoption on transport harvest activities is about 4 man-days, while the labor effect for the furrowing land preparation activity is only an additional 1 man-day. This result follows Proposition 4 in our theoretical model where we posit that the expected mean yield increase from GM crop adoption is likely to increase harvest time labor use more than pre-harvest non-pest management labor.

Lastly, comparing the pre-harvest land preparation labor effects of single-trait adoption versus stacked trait adoption (i.e., comparing the third and fourth column of the top panel in Table 3.5), it should be noted that adoption of the stacked variety had a larger effect on the pre-harvest land preparation labor time relative to the single-trait variety. To interpret this, we note that Shi et al. (2013) using data from field experiments have indicated that the stacked Bt/HT variety tend to have a stronger variance reducing effect as compared to single-trait Bt corn, while Bt tends to have a higher mean yield increasing effect. In addition, using our own survey data, we also find that the variance-reducing effect of adopting stacked Bt/HT corn tend to be higher than that of a single-trait Bt corn, while the mean increasing effect tends to be stronger for the single trait Bt variety (see Table A9). [34]

Combining this with Figure 3.1 (Corollary 3) we see that the relative size of the coefficients of Bt corn adopting farms and stacked adopting farms (the stacked adopting farms had a larger pre-harvest response than the Bt adopting farms) likely suggests that the farms are to the left of the intersection point. This means that the farms are sufficiently small such that they will be more sensitive to changes in risk than to changes in mean yield. This again seems plausible given the sizes of the farms represented in the data. The mean farm size in the sample is 1.4 hectares with the largest farm being 8 hectares, which is relatively small compared to the mean farm size of 175 hectares in the US, for example. The result above is therefore consistent with the notion that a stronger expected variance-reducing effect of a specific GM crop variety (like the stacked Bt/HT) would lead to a larger pre-harvest, non-pest management labor response for farms of this size. Weaker significance in the harvest period for the stacked variety compared to the single trait Bt variety also conforms to

[34] Note that we use the procedure described in Just and Pope (1977) to estimate the effects of GM crop adoption on mean yield and yield variance. The production function is assumed to follow the following: $y = f(x;\alpha) + h(z;\beta)\varepsilon$, where *y* is yield, *x* are variables that affect the mean yield (represented by the *f* mean function), *z* are variables that affect the variance represented by the *h* mean function), α and β are parameters to be estimated, and ε is the error term. Both $f(x;\alpha)$ and $h(z;\beta)$ are assumed to take the form of a Cobb Douglas production function. Standard assumptions in the literature and in our own conceptual framework is that farm yield is heteroskedastic. Figure A.1 and Table A.10 show evidence of this assumption holding. To account for this, standard practice for estimating Just Pope models requires the use of predicted values from a second stage log variance equation as weights in the first stage to control for the non-uniform variance of yield. This is the method we use. The results of the Just Pope estimations are presented in Table A.9.

the notion of Bt having a bigger yield increasing effect. This also implies that these farms are more responsive when risk is reduced than if mean yield (and possibly income) is increased.

3.5.4. Effects of GM Varieties on Operator, Family, and Hired Labor, by Production Activity

In the previous sub-section, we discussed the effect of GM crop adoption on the total labor man days used (e.g., sum of operator, family, and hired) for each on-farm production activity. But are the labor effect patterns observed above for total labor the same for specific labor types? In Table 3.6 to Table 3.8, we present the estimated effects of single-trait Bt adoption and stacked Bt/HT adoption on labor used for each production activity, separated out by labor type – effects on operator labor in Table 3.6, effects on family labor in Table 3.7, and effects on hired labor in Table 3.8.

In general, the pattern of effects observed for total labor use (as discussed in the previous sub-section) is also observed for operator labor and hired labor, but not for family labor. First, operator and hired labor used for pest management-related tasks tend to fall with GM crop adoption (Proposition 1). Second, the labor increasing effects of GM crop adoption (due to the complementary labor crowd-in mechanisms) are also observed for the non-pest management activities of operator and hired labor (Propositions 2 and 3). Third, the magnitude of the positive harvest labor effects tend to be larger than the magnitudes of the positive pre-harvest non-pest management effects for both operator and hired labor (Proposition 4). Fourth, the positive effect of stacked Bt/HT adoption on operator and hired labor used for pre-harvest land preparation is greater than the corresponding effect of single-trait Bt adoption (i.e., due to the stronger response to the variance reducing effect of the stacked corn variety; see Corollary 3). Taken altogether, these results imply that farm-operators are now willing to spend more time on their farm, and hire more labor, when they adopt GM crop varieties that they perceive will provide higher yields and/or lower yield variability.

However, with regards to GM adoption effects on family labor, it seems that the pattern observed for total labor, operator labor, and hired labor is not readily apparent in the family labor results presented in Table 3.7. Most of the estimated family labor effects of single-trait Bt and stacked Bt/HT adoption are statistically insignificant (Table 3.7). This is perhaps consistent with the report in Gerpacio et al. (2004) citing that farmers may wish to generate income to send their children to school. Therefore, time saved on the farm frees up time for family members, other than the operator to pursue other activities, which may include spending more time in school. Nevertheless, the largely insignificant family labor effects suggest that labor use effects of GM crop adoption apply more for operator and hired labor, rather than family labor.

3.5.5. Risk Preferences and the Marginal Response to Changes in Mean Yield and Yield Risk

Finally, to identify responses to risk vs responses to mean yield (mean income) changes, we exploit features of the data that allow for this. As mentioned earlier, we found the stacked variety to have a stronger risk reducing effect than the Bt variety, while the single trait Bt variety has a stronger mean increasing effect (Table A9). Corollaries 2 and 3 give us ways to distinguish between a pre-harvest on-farm labor response that is the result of changes in risk (i.e. variance reduction) and ones that are the result of changes in mean yields. Corollary 2 predicts that for DARA preferences, the response to increases in expected yield is increasing in wealth. Corollary 3 predicts that the on-farm labor response to changes in risk decreases as farm wealth increases.

We use accumulated farm assets[35] as a measure of farm wealth to test changes in the parameter of risk aversion. Corollary 2 predicts that the pre-harvest (non-pest management) on-farm labor response to a mean yield increase (proxied by Bt adoption in our case) should be increasing in wealth (i.e., the effect of mean yield on labor is larger for larger/wealthier farms). On the other hand, the pre-harvest (non-pest management) on-farm labor response to reduction in yield risk/variance (proxied by stacked adoption) is decreasing in this measure of wealth (i.e., the labor increasing effect of yield risk reduction is smaller for larger/wealthier farms). Table A.7 and Table A.8 show the results of this test[36]. The estimation procedure in Table A.7 assumes a linear response and uses an interaction between wealth and the adoption variable to test how the marginal effect of Bt and Bt/HT adoption changes as wealth changes. Table A.8 on the other hand assumes a monotonic non-linear response of risk sensitivity to changes in wealth, and uses the log of farm wealth in the same interaction. The results in both tables are similar, but those in Table A8 produce statistically significant results suggesting the effect may be non-linear.

From Table A8 shows the coefficients on the Bt and Bt/HT interactions are positive and negative, respectively (for most pre-harvest tasks). The signs conform to the predictions

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[35] Assets included were farm equipment such as tools, generators, hand tractors and the value of farm land. Using current off-farm income or farm revenues as a measure of wealth is a direct function of current farm labor decisions and will therefore produce biased results. Accumulated assets will better measure the state of farm holdings but does not directly enter the farm profit function.

[36] Results for the farm operator are presented. While the results for the other labor types are largely similar, the results lacked statistical power. This may suggest that the farm operator, being the primary decision maker on the farm is most sensitive to the incentive-changing events on the farm.

made in Corollaries 2 and 3, if farmers have DARA preferences with the sign on our proxy for changes in risk (the stacked dummy) being negative in the pre-harvest phase, while our proxy for changes in mean yield (the Bt dummy) is generally positive. This supports the idea of farmers with DARA preferences, but also showing that the wealth effect is likely non-linear. The interaction with Bt however, is not significant (neither in the linear nor non-linear specification). This may be the result of lack of statistical power, or may suggest features that are not directly implied by our model, or may potentially imply that an off-setting risk reducing impact exists that we were not able to detect in our Just Pope estimations.

Nevertheless, the results lend strong support for our assumption of Bt being primarily mean yield increasing variety while the Bt/HT variety affects pre-harvest incentives primarily through the risk/variance reduction channel. It also supports the idea that farmers exhibit DARA preferences. Importantly, the effect of the Bt/HT variety vanishes in the harvest period as would be expected since Corollary 5 predicts that a direct risk effect is only present in the pre-harvest period (any labor responses in the harvest period would be the result of a yield increase due to adjustments in the pre-harvest period and would not depend on risk preferences at that point). This seems to imply that changes that we observe in our sample are at least partially explained by the risk and yield feedbacks we posit.

3.6. Conclusions and Implications

This study carefully explores how single-trait and stacked GM crop adoption influence on-farm labor allocation. A theoretical model is developed to show that the overall impact of GM crops on labor use will depend on the relative magnitudes of two competing effects: (1)

a direct substitution effect that reduces labor used for pest management activities, and (2) a positive complementary labor crowd-in effect that increases labor used for land preparation and harvest time activities. The latter effect is mainly due to the expected mean yield increase and the variance reduction associated with the adoption of single-trait Bt and stacked Bt/HT crops.

Using a two-year panel data set from GM and non-GM corn farmers in the Philippines, we find that labor crowd-in effects outweigh the labor-saving effect. That is, the positive labor impact of GM crop adoption on non-pest management activities (like land preparation and harvest time activities) is greater than the labor use reduction for pest management-related activities. The positive labor crowd-in effect due to expected mean yield increases is also more strongly felt for harvest time activities rather than pre-harvest land preparation activities. Moreover, the pattern of effects observed for total labor use is apparent for the allocation of operator labor and hired labor (but not for family labor). Differences in the effects the two GM crop varieties in the sample also allowed us to identify separately the isolate differences in farmer responses to changes in yield risk (e.g., variance) versus changes in mean yield. Our results show incentive feedbacks created through changes in yield distribution of the GM crops are important in determining post adoption behavior of farmers. In this case, we show how it specifically affects the decision to utilize labor on the farm, in both the pre-harvest and harvest periods. We also show that farms of the size represented in this sample are more sensitive to changes in risk in the pre-harvest phase than to changes in mean yield.

Results of this study have important implications for the GM crop literature and the debate about the potential benefits of GM crop technology. GM crops are normally thought of as a labor-saving technology since they directly substitute for the labor used for controlling some crop pests. Though several studies (see, for example, Gardner et al., 2009; Rice 2004; Aldana et al. 2012; Wu 2004; Huesing and English 2004; Smale, Zambrano and Cartel 2006) have empirically shown that there are indeed cases where adoption of GM crops have reduced on-farm labor use, a number of studies in multiple contexts also show that GM crop adoption can also increase total labor use or do not significantly affect overall on-farm labor use. Our study fills a gap in the literature by exploring the mechanism that helps to explain these varying results. We show that the effect of GM crop adoption on farm labor allocation is more nuanced than previously thought – influencing not just the pest management-related labor allocation, but also the land preparation and harvest time labor allocation indirectly. Therefore, while pesticidal GM crops have labor-saving features, the overall effect will depend on the context of adoption and the effect of the specific GM crop on the distribution of yield.

Our conclusion that small farms are more sensitive to changes in risk exposure in the pre-harvest period than to changes in expected mean productivity also has important implications. These findings provide valuable information for policy makers concerned with encouraging small farm development, particularly in lower-income countries like the Philippines. Evidence from our study suggests that controlling risk has a greater impact in a farmer's decision to invest time and effort on the farm. As pests tend to be a bigger problem in warmer tropical countries (like the Philippines) than in temperate northern ones, the ability to control such risks could prove to be very important for the productivity of small farms in these areas. Hence, our results suggest that it may be important for policy makers to create mechanisms to encourage pest-risk reduction strategies, in order to enhance on-farm productivity and spur economic development in agriculture. The importance of the risk channel in labor decisions may also signal the importance of risk in willingness to invest in other resources (other than time) on the farm. This question will be an interesting next step in understanding the impact of the risk and mean yield channels and the impact of GM crops in general on farmer incentives.

Although we provide fairly compelling evidence about the labor increasing effects of GM corn based on data from the Philippines, we recognize that several questions remain. The non-compliance of family labor to some of the theoretical predictions has been a finding in previous studies and is left unresolved here. This lack of response of family labor time may reflect differences in opportunities of family members off of the farm (i.e., farm family members, other than the farm operator and spouse, on average have attained at least a high school level of education in our data, which is greater than educational levels of the farm operator and spouse in general). This may also hint at the possibility of family labor being "fixed", to allow them to take advantage of other opportunities or fulfill obligations not related to farming. Gerpacio (2004) also mentions the desire of families in the Philippines to educate their children making them less tied to this farm. This may also help drive results. Future work may want to consider substitution patterns among labor types and perhaps account for varying productivity among these types on the farm. Describing results in terms of labor product would help to more meaningfully describe the extent of labor crowd-in effects.

Another area for future research would be to investigate the labor effects for different GM crops (i.e., cotton, soybean; and with multiple traits aside from Bt and HT). In addition, investigating this labor effect issue using larger farm-level survey data (with more observations over space and time) would likely provide more statistical power to show more statistically significant effects. Obtaining a panel dataset with multiple adjacent years would also allow for the ability to account for time dynamics that may result from new adopters adjusting and learning the technology. If these dynamics can be accounted for, then it may allow for more precise estimates of the GM adoption effect on labor. We leave this for future work.

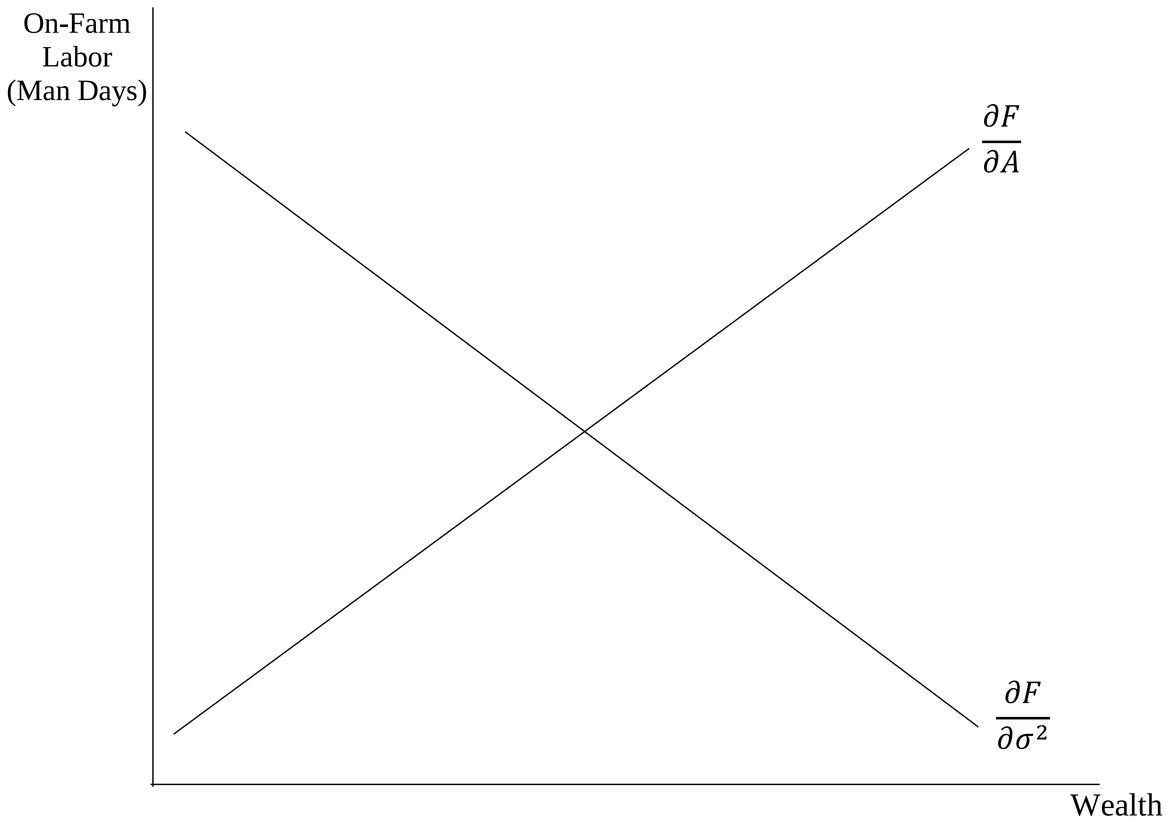

Figure 3.1. On-farm Labor Response to Changes in Yield Risk (e.g. variance) and Expected Mean Yield Depends on Sensitivity to Risk.

[Note: For farmers with DARA preferences, sensitivity to risk decreases as farm income increases. Figure 3.1 shows that at low levels of income, on-farm labor responds more to changes in risk than changes in expected mean yield. However, at higher levels of income the reactions will eventually switch]

Table 3.1. Descriptive Statistics: Mean Labor Time (man-days) Across Labor Types

Labor Type	First Survey Year		Second Survey Year		
	Hybrid 2007	Bt only 2007	Hybrid 2010	Bt only 2010	Stacked 2010
	---- Labor time in Man-days ----				
Operator Labor	0.41	0.97	0.48	2.46	5.11
	(0.724)	(2.061)	(0.995)	(3.719)	(6.955)
Family Labor	12.34	7.32	32.66	11.59	6.21
	(9.286)	(6.460)	(24.10)	(13.59)	(14.91)
Hired Labor	25.68	48.35	32.06	32.21	32.62
	(17.12)	(38.42)	(20.87)	(32.20)	(37.58)
Total (all labor types)	38.43	56.64	65.21	46.26	43.94
	(19.40)	(39.95)	(32.13)	(34.13)	(39.97)
No. of Obs.	109	146	22	21	212

Note: (1) Standard deviations in parentheses.

Table 3.2. Descriptive Statistics: Mean Labor Time (man-days) Across Different Production Activities

Production Activities (for all labor types)	First Survey Year		Second Survey Year		
	Hybrid 2007	Bt only 2007	Hybrid 2010	Bt only 2010	Stacked 2010
	---- Labor time in Man-days ----				
Land Prep. Activities	8.04	11.90	18.11	10.69	9.69
	(5.952)	(8.938)	(13.83)	(6.414)	(9.533)
Pesticide Application	2.49	1.61	0.23	0.10	0.05
	(2.805)	(1.637)	(0.685)	(0.301)	(0.340)
Weeding	2.64	0.34	9.05	3.74	1.09
	(5.042)	(1.037)	(10.25)	(6.127)	(5.756)
Herbicide Application	0.69	1.72	0.50	2.02	1.63
	(0.967)	(1.952)	(1.024)	(2.461)	(2.679)
Fertilizer Application	3.73	4.86	6.33	3.51	5.62
	(3.445)	(3.154)	(4.893)	(1.865)	(6.387)
Harvest Activities	19.18	29.80	27.44	23.94	23.73
	(9.911)	(33.71)	(16.02)	(23.02)	(24.09)
No. of Obs.	109	146	22	21	212

Notes: (1) Standard deviations in parentheses, (2) Land Prep. activities include labor time for the following: plowing, harrowing, furrowing, (3) Harvest activities include labor time for the following: De-husking, bagging, shelling, cutting, monitoring, loading, hauling and transport.

Table 3.3. Descriptive Statistics: Mean Farm/Farmer Characteristics included in the Empirical Specification (by GM variety and Survey Year).

Labor Type	First Survey Year		Second Survey Year		
	Hybrid 2007	Bt only 2007	Hybrid 2010	Bt only 2010	Stacked 2010
Expected Yield	3903.47	5463.16	6177.50	8175.95	5971.34
	(1949.1)	(1617.6)	(2825.9)	(6437.2)	(2529.9)
Realized Yield	3768.98	4881.47	4176.72	8325.69	6090.40
	(1712.7)	(1678.5)	(1727.0)	(3693.7)	(4814.9)
HH Size	4.76	4.43	5.09	5.29	4.77
	(1.644)	(1.504)	(1.998)	(2.327)	(1.675)
Hectares Planted	1.00	0.98	1.36	1.10	1.06
	(0.576)	(0.593)	(0.699)	(0.852)	(0.999)
Area of Farm (HA)	1.28	1.48	1.47	1.26	1.42
	(0.722)	(0.887)	(0.705)	(0.922)	(1.172)
Off Farm: Family	2725.68	4043.88	3669.09	10574.00	4203.32
	(5298.3)	(8368.7)	(3388.4)	(13688.9)	(8510.2)
Off Farm: Farmer	682.23	948.47	2450.00	4234.95	1723.44
	(1408.2)	(1781.4)	(2265.4)	(9014.7)	(4813.5)
No. of Obs.	109	146	22	21	212

Note: (1) Standard deviations in parentheses, (2) *Bt* – dummy variable = 1 if adopted Bt only variety (=0 otherwise); *Stacked* – dummy variable = 1 if adopted Stacked Bt/HT variety (=0 otherwise); *HH_Size* – Household size, *Acres* – total no. of corn acres; *Owner* – dummy variable = 1 if corn acres is owned by the operator (=0 otherwise); *Off_family* – Off-farm income of family members (in Philippine Pesos); *Off_farmer* – Off-farm income of operator(in Philippine Pesos); *2011_Year* – dummy variable = 1 if survey year =is 2011 (=0 otherwise)

Table 3.4. Effect of GM Variety Adoption on Total Labor Used (in man-days) for All Production Activities, by Labor Types (e.g., Operator, Family, Hired, and All Types).[1]

Labor Type	Estimated effect of single-trait Bt variety on total labor used for all production activities[2]	Estimated effect of Stacked Bt/HT variety on total labor used for all production activities[2]
Operator	2.39* (2.26)	3.42+ (1.82)
Family	0.02 (0.01)	-5.22 (-1.11)
Hired	9.93+ (1.67)	19.87+ (1.89)
All Types (sum labor for all types)[3]	12.34+ (1.90)	18.07 (1.57)

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{St} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Table A.2. In addition, the parameter estimates for operator, family, and hired labor were estimated using the Fixed Effects-SUR approach (see equations 11-13), while the parameter estimates for All Types is based on a Fixed Effects approach since we are aggregating all labor types in this case (see equation 10).
[2] Figures in parentheses are t-statistics: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.
[3] This reflects the sum of all labor use for all types (i.e., aggregate labor time spent by all labor types) and across all production activities conducted within the season.

Table 3.5. Effect of GM Variety Adoption on Total Labor Hours Used (in man-days) by Production Activity for All Labor Types (i.e., aggregate of operator, family, and hired labor)[1]

Production Activities	Estimated effect of single-trait Bt variety on total labor used for by production activity[2]	Estimated effect of Stacked Bt/HT variety on total labor used by production activity[2]
Land Prep. Activities		
Land Preparation	0.19	1.87
	(0.23)	(1.33)
Harrowing	-0.25	0.25
	(-0.80)	(0.46)
Furrowing	0.40	1.34*
	(1.09)	(2.08)
Planting	1.39	2.15
	(1.09)	(0.96)
Pest Mgt. and Fert. Activities		
Herbicide application	0.82+	0.49
	(1.84)	(0.63)
Weeding	-2.17+	-1.44
	(-1.93)	(-0.72)
Pesticide application	-0.04	-0.14
	(-0.13)	(-0.25)
Fertilizer application	-0.39	-0.09
	(-0.44)	(-0.06)
Harvest Activities[3]		
Processing	5.86	11.28
	(1.19)	(1.29)
Transport/Hauling	3.84**	3.53
	(3.03)	(1.58)
Combined Harvest	9.70+	14.81
	(1.87)	(1.62)
No. of Obs.	510	510

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{St} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Table A.3. In addition, the parameter estimates above is based on a Fixed Effects approach since we are aggregating man-days for all labor types (see equation 10) and not separately estimating by labor type.
[2] Figures in parentheses are t-statistics: * p<0.10, ** p<0.05, *** p<0.01.
[3] The "Processing" harvest activity includes such tasks as: cutting, de-husking, bagging, shelling, monitoring and guarding. The "Transport/Hauling" harvest activity includes such tasks as: hauling, loading, unloading, and transporting of harvested corn.

Table 3.6. Effect of GM Variety Adoption on Operator Labor Hours (in man-days) by Production Activity[1]

Production Activities	Estimated effect of single-trait Bt variety on total labor used for by production activity[2]	Estimated effect of Stacked Bt/HT variety on total labor used by production activity[2]
Land Prep. Activities		
Land Preparation	0.48	0.97+
	(1.55)	(1.77)
Harrowing	0.20+	0.32+
	(1.92)	(1.70)
Furrowing	0.22+	0.48*
	(1.92)	(2.42)
Planting	-0.07	-0.30*
	(-1.03)	(-2.39)
Pest Mgt. and Fert. Activities		
Herbicide application	-0.05	-0.20
	(-0.24)	(-0.54)
Weeding	-0.05	0.02
	(-0.46)	(0.09)
Pesticide application	-0.09**	-0.08
	(-3.00)	(-1.42)
Fertilizer application	-0.24+	-0.17
	(-1.69)	(-0.67)
Harvest Activities[3]		
Processing	2.18**	2.90*
	(2.79)	(2.09)
Transport/Hauling	0.16	0.21
	(1.10)	(0.82)
Combined Harvest	2.35**	3.11
	(2.92)	(2.18)
No. of Obs.	510[4]	510[4]

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{St} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Table A.4. In addition, the parameter estimates above is based on the Fixed Effects-SUR approach that simultaneously estimate the GM variety effect on operator, family, and hired labor (see equations 11-13).

[2] Figures in parentheses are t-statistics: * p<0.10, ** p<0.05, *** p<0.01.

[3] The "Processing" harvest activity includes such tasks as: cutting, de-husking, bagging, shelling, monitoring and guarding. The "Transport/Hauling" harvest activity includes such tasks as: hauling, loading, unloading, and transporting of harvested corn.

[4]Observations count represent 255 first differenced observations from 510 sampled farmers.

Table 3.7. Effect of GM Variety Adoption on Family Labor Hours (in man-days) by Production Activity[1]

Production Activities	Estimated effect of single-trait Bt variety on total labor used for by production activity[2]	Estimated effect of Stacked Bt/HT variety on total labor used by production activity[2]
Land Prep. Activities		
Land Preparation	0.18	-0.23
	(0.37)	(-0.28)
Harrowing	0.03	0.13
	(0.16)	(0.40)
Furrowing	0.07	-0.32
	(0.35)	(-1.02)
Planting	-0.24	-0.80
	(-0.63)	(-1.16)
Pest Mgt. and Fert. Activities		
Herbicide application	0.23	-0.02
	(1.29)	(-0.05)
Weeding	-0.46	-0.72
	(0.58)	(-0.51)
Pesticide application	-0.15	-0.02
	(-0.69)	(-0.05)
Fertilizer application	-0.49	-1.95**
	(-1.14)	(-2.60)
Harvest Activities[3]		
Processing	0.74	0.04
	(0.55)	(0.02)
Transport/Hauling	0.26	0.65
	(0.42)	(0.58)
Combined Harvest	1.00	0.69
	(0.60)	(0.23)
No. of Obs.	510[4]	510[4]

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{St} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Table A.5. In addition, the parameter estimates above is based on the Fixed Effects-SUR approach that simultaneously estimate the GM variety effect on operator, family, and hired labor (see equations 11-13).

[2] Figures in parentheses are t-statistics: * p<0.10, ** p<0.05, *** p<0.01.

[3] The "Processing" harvest activity includes such tasks as: cutting, de-husking, bagging, shelling, monitoring and guarding. The "Transport/Hauling" harvest activity includes such tasks as: hauling, loading, unloading, and transporting of harvested corn.

[4]Observations count represent 255 first differenced observations from 510 sampled farmers

Table 3.8. Effect of GM Variety Adoption on Hired Labor Hours (in man-days) by Production Activity[1]

Production Activities	Estimated effect of single-trait Bt variety on total labor used for by production activity[2]	Estimated effect of Stacked Bt/HT variety on total labor used by production activity[2]
Land Prep. Activities		
Land Preparation	-0.47	1.15
	(-0.96)	(1.32)
Harrowing	-0.48**	-0.20
	(-2.96)	(-0.70)
Furrowing	0.12	1.20*
	(0.43)	(2.52)
Planting	1.71	3.26
	(1.40)	(1.51)
Pest Mgt. and Fert. Activities		
Herbicide application	0.65*	0.71
	(2.06)	(1.30)
Weeding	-1.66**	-0.73
	(-2.72)	(-0.68)
Pesticide application	0.20	-0.04
	(1.26)	(-0.14)
Fertilizer application	0.33	2.03
	(0.40)	(1.42)
Harvest Activities[3]		
Processing	2.94	8.34
	(0.68)	(1.09)
Transport/Hauling	3.41***	2.68+
	(3.80)	(1.68)
Combined Harvest	6.35	11.01
	(1.41)	(1.38)
No. of Obs.	510[4]	510[4]

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{St} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Table A.6. In addition, the parameter estimates above is based on the Fixed Effects-SUR approach that simultaneously estimate the GM variety effect on operator, family, and hired labor (see equations 11-13).

[2] Figures in parentheses are t-statistics: * p<0.10, ** p<0.05, *** p<0.01.

[3] The "Processing" harvest activity includes such tasks as: cutting, de-husking, bagging, shelling, monitoring and guarding. The "Transport/Hauling" harvest activity includes such tasks as: hauling, loading, unloading, and transporting of harvested corn.

[4]Sample size is 255 differenced observations from original sample of 510 observation

CHAPTER 4

Bioeconomic Feedbacks from Large-Scale Adoption of Transgenic Pesticidal Corn in the Philippines

4.1. 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 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 respond 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 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 2007b; Timmins and Murdock 2007; Allen 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’

[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.

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. A more appropriate description of this concept is to think of a negative or ‘congestion’ effect associated with adoption shares to be an example of farmers taking advantage of a public good. The public good here being pest damage abatement provision by other farmers’ adoption decisions. On the other hand, a positive or ‘agglomeration’ effect may be associated with several effects, two of which would be information sharing or damage avoidance. Damage avoidance would be most likely associated with the stacked variety if increased use of herbicides increases damage to neighboring farms. However, to be consistent with the sorting literature, we maintain the use of the terms congestion and agglomeration, while the meanings we described above are the ones implied.

Of course, 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 (2007a). This technique utilizes area-level variation in exogenous characteristics and choice sets to instrument for area-wide adoption, and then uses these instrumented adoption shares as inputs to a random utility model (RUM) of individual adoption choice. 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, 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 (Bayer and Timmins 2007b).

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 allow us to identify 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.

4.2. 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 has comprised a major research topic 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. (Brito, Sheshinski and Intriligator 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 (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 (Bayer and Timmins 2005; Bayer and Timmins 2007b) 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, regardless of distributional assumptions and functional form as long as sufficient variation in alternatives 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.

4.3. 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.

4.3.1. 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: 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, 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 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 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 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

[3] 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, Bt crops are definitively pest suppressing, as previously discussed, and not repelling at an area-wide scale.

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 4.1 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.

4.3.2. Econometric model

To empirically evaluate the presence of agglomeration or congestion effects, we apply an IV method developed by Bayer and Timmins (2007a) 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}:

$$U_{jih} = \beta x_{ji} + \delta_{jh} + \epsilon_{jih} \tag{3}$$

with the associated decomposition of area-level effects:

$$\delta_{jh} = \alpha C_{jh} - \eta p_{jh} + \xi_{jh} \tag{4}$$

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 adopting 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

[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.

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 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 adoption 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 $\mathrm{Cov}(C_{jh}, \xi_{jh}) \neq 0$. As Timmins and Murdock (Timmins and Murdock 2007) point out, the tendency is for $\mathrm{Cov}(C_{jh}, \xi_{jh}) > 0$, 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, 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.

[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.

The IV approach proposed by Bayer and Timmins (2007a) 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 constructed as follows:

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

where $\tilde{\beta}$ and $\tilde{\eta}$ are initial 'guesses' of their respective parameters. Bayer and Timmins show 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). This is the approach we use here.

4.4. 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 and 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. (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

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 adoption, 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.

The survey was confined to the provinces of Isabela and South Cotabato, both major corn-producing provinces with a high level of Bt adoption. The non-Bt farmers in our data are strictly hybrid corn users. 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. 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 source and nearest road in the first-stage estimation, following Sanglestsawai et al.'s (Sanglestsawai et al. 2014a) 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.

To obtain variety-specific prices which vary by area, we use an approach similar to Bayer et al. (2009) and Klaiber and Phaneuf (Allen Klaiber and Phaneuf 2010). We regress 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.

4.4.1. Summary statistics

Table 4.1 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 4.2 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 4.3 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%.

4.5. Econometric estimation

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

4.5.1. 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 use the same approach proposed by Timmins and Murdock (Timmins and Murdock 2007). Their approach to this problem is first to 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 $\hat{\delta}_{jh}$. They then adopt an IV median (quantile) regression in the second-stage in place of a two-stage least squares, to avoid the problem of the large-magnitude boundary $\hat{\delta}_{jh}$'s creating outlier problems in the regression. They 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*.

One concern with using the setting of values at the boundaries and the use of the median regression is that the small value used to correct for observations of 0 and 1 and the use of the median regression in the second stage may, in fact, be driving results. To address this concern, we substitute the first stage estimation strategy with a linear model instead of the conditional logit procedure. The fixed effects from this model (triple interaction of village year and variety fixed effects) are then used to generate $\bar{\delta}_j$'s from the original specification which are then used in the second stage to estimate the spillover effect. While we expect to lose some statistical power due to the lack of a distributional assumption as is the case with the conditional logit, we do expect the results to be similar in a qualitative sense. We do confirm this and present these results in Appendix C.

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.

4.5.2. Estimation results

We start by presenting results from the first-stage conditional logit model, with and without area-level fixed effects (

Table 4.4). 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 4.4, 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

Table 4.4 and Table 4.5 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.

Figure 4.1 and Figure 4.2**,** the instrument performs well, in terms of providing significant explanatory power for empirical adoption shares.

Table 4.5 provides estimates from the second stage regression, with the five different ways of handling the spillover effect. All five specifications use a median regression 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 4.3.1. 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 4.5). 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 are not in 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. Table 4.6 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.

4.6. 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 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 econometrically 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. Our research points out that 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

[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.

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, 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. (2012b). 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; Qiao 2015; Sanglestsawai et al. 2014a). While much of this econometric work addresses the potential endogeneity of Bt adoption owing to selection, our research suggests there may 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.

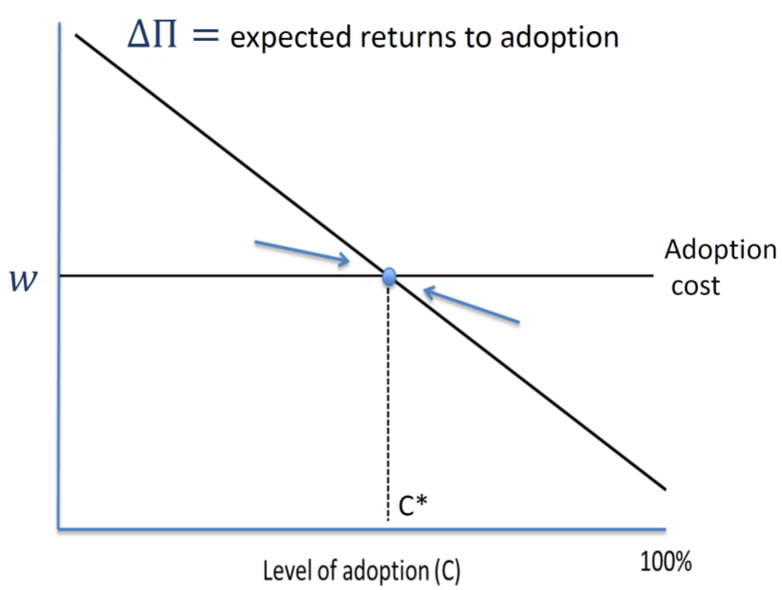

Figure 4.1. Illustration of a Negative Economic Feedback from a Pest Suppression Spillover.

Table 4.1. 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 4.2. 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 4.3. 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.

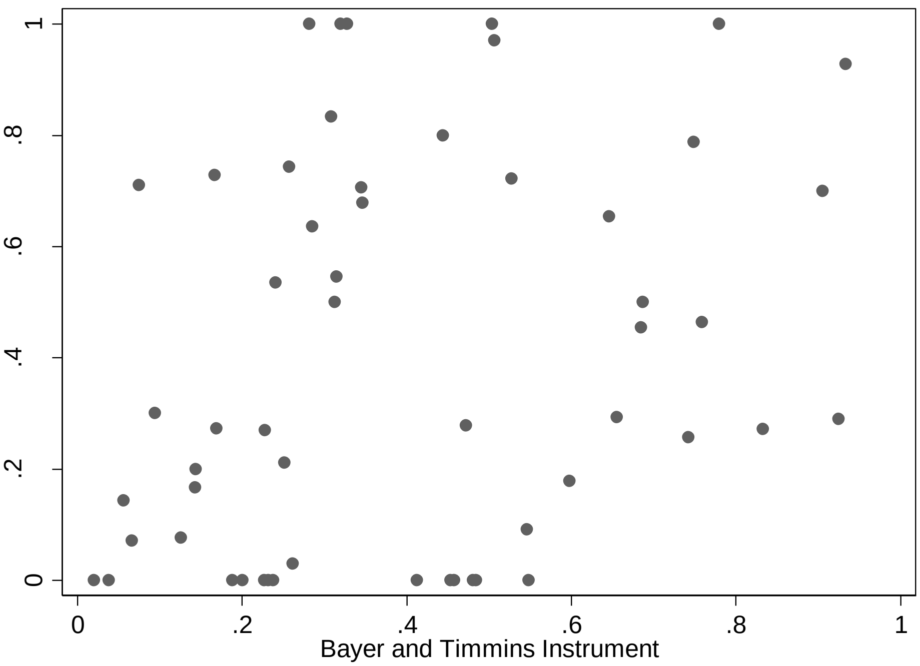

Figure 4.2. Village-Level Adoption, Empirical vs Instruments

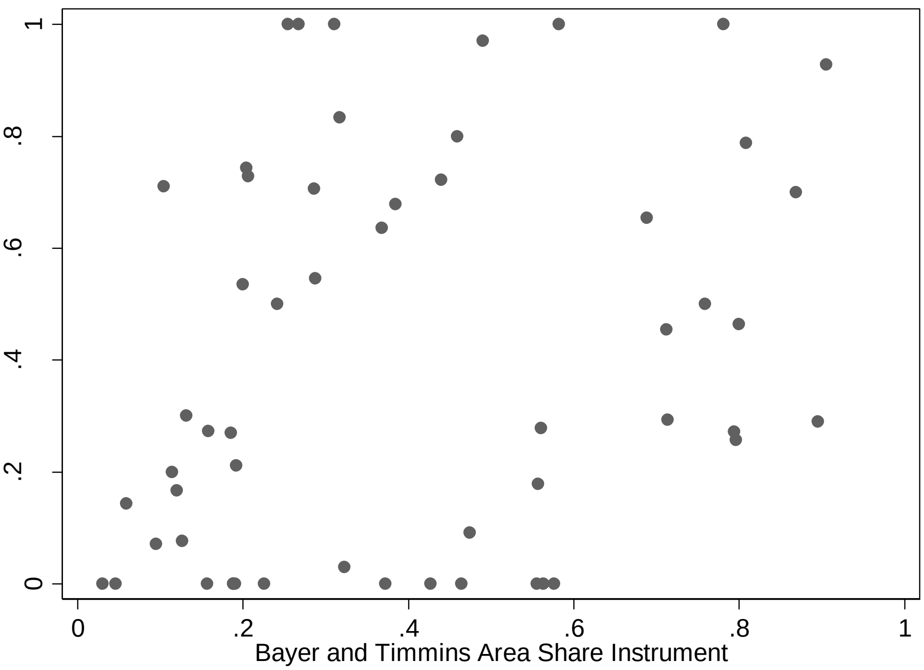

Figure 4.3. Village-Level Adoption, Empirical vs Instrumented Area-Weighted Shares

Table 4.4. 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 4.5. 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 (PHP)	-0.0101	-0.0144	-0.00323	-0.0203	-0.0961**
	(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 2007b).

Table 4.6. 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%

CHAPTER 5

Conclusions

This dissertation is intended to show the existence of post adoption feedbacks on the decisions made by commercial GM corn farmers in the Philippines. It shows that feedbacks can exist intertemporally on the same farm as well as across farms through influences on crucial factors such as area-wide pest pressure. The dissertation explores these two specific issues, with Chapter 3 exploring the impact of income and risk exposure effects of GM crops on intertemporal labor decisions. Chapter 4 investigates the impact of the decisions of adopting farmers on the decisions of non-adopting farmers in a public goods provision framework. The public good in this case is the provision of pest damage abatement by adopting farmers. In these two cases mechanisms that help to explain the existence of these effects are explored and estimates of the observable impacts are presented.

Chapter 2 provides an overview of the context of the farmers in the sample. It discusses the characteristics of Filipino corn farmers in general, their importance to the Filipino economy and the size, habits and institutional support of corn farmers in the Philippines. The chapter concludes by comparing the farmers sampled in the data used for this dissertation with the discussion of the farmers at the national level. The goal of this discussion is evaluate the representativeness of the sampled farmers of the population of commercial yellow corn farmers at the national level in the Philippines.

5.1. Own Farm Feedbacks on Labor Incentives

Chapter 3 investigates the proposition of GM crops being predominantly labor saving. It shows that GM crops geared towards pest management have two competing channels that affect labor time on the farm. A labor-saving channel introduced from reduced need to manually manage pests. A second channel, previously underexplored, are the effect that productivity increases and risk reductions typically associated with GM crop adoption can have on the perceived marginal product of farm labor. Changes to the marginal product of labor can crowd-in the use of labor on the farm and counteract the labor savings produced by the GM crops. While it has been recognized that this effect should exist in the harvest phase (since more labor would potentially be required to handle the increased yield at the end of the cropping season) our theoretical framework suggests that the effects should also be evident in the pre-harvest phase of the farming cycle as well. The sum of labor impacts in these two phases has the potential to outweigh reductions in pest management labor produced by the crop. The model also suggests that the overall sum of effects will depend on the effects of the crop on the yield distribution and the utility for risk of the farmers which will depend on their wealth and access to other risk management tools.

The findings in this chapter suggest the importance of risk exposure to poorer farmers in the Philippines, as the sensitivity to risk was seen to be greater than the sensitivity to increases in productivity. While the effect on labor time is evident from this study, the findings here may also suggest that the features of GM crops that led to the changes in labor time may also affect other decisions that are sensitive to risk. These include farm investments or potentially the ability to access educational opportunities for children, since, as shown in

Chapter 2, the return to education in the Philippines appears to be high. This means that estimates of the welfare impacts of GM likely change (perhaps increase) over time since the return to some of the benefits to farmers adopting GM crops may not be realized until several years post adoption. Current welfare impact assessments, should therefore incorporate this forward-looking approach to obtaining estimates.

5.2. GM Impact Spillovers to Neighboring Farms

While Chapter 3 investigated secondary impacts that GM corn adoption can have on the adopting farm, Chapter 4 on the other hand explores how GM impacts can spillover to neighboring farms. As pointed out in Hutchison et al. (2010), Bt trait GM varieties are very effective at eliminating target pests. As the number of adopters increases, the effect of pest reduction is experienced at the area level. This means that farmers who have not adopted the Bt corn variety can also experience a reduction their costs of pest management because of the adoption decisions of neighboring farmers. This public good provided by adopting farmers creates a free rider problem, where non-adopting farmers have incentive to forgo the cost of adoption (GM seeds cost as much as 3 times as much as hybrid seeds in the sample used) while still experiencing a reduction in pest pressure provided by Bt adopters. This means that the incentive to adopt likely decreases as area level adoption of varieties containing the Bt gene increases.

We present an instrumental variables estimation procedure, frequently used in the hedonic literature but uncommon in the agricultural literature, to estimate the endogenous spillover effect of area level Bt corn adoption in the Philippines. We recover an effect that suggests that the willingness to pay for Bt corn decreases by between 13 and 40 PHP per kilogram as Bt adoption rates increase by 10% (depending on whether the share measures per farm adoption or farm area adoption rates). The weighted measure is likely an overestimate of the spillover value as some area on additional plots is unaccounted for in the area weighted calculation as pointed out in Chapter 2.

Findings in this study imply that the welfare impacts of Bt corn technology is further reaching than might previously have been considered. While welfare assessments would naturally consider the effects on adopting farms, the findings in Chapter 4 suggest that the effects on non-adopting farms also exist. Ignoring these effects likely biases welfare estimates of GM crops. However, even though this first primary consideration of the issue suggests welfare impacts may increase, other issues such as impacts on predator/prey dynamics are left unexplored here. Thus, a full treatment of the welfare effects of Bt should take all of these dynamics into account. Nevertheless, our findings here bring to the forefront an effect which, to this point, has been largely underexplored and unaccounted for in the literature. Future work must be geared towards understanding how these effects change previous welfare currently and over time.

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APPENDICES

Appendix A

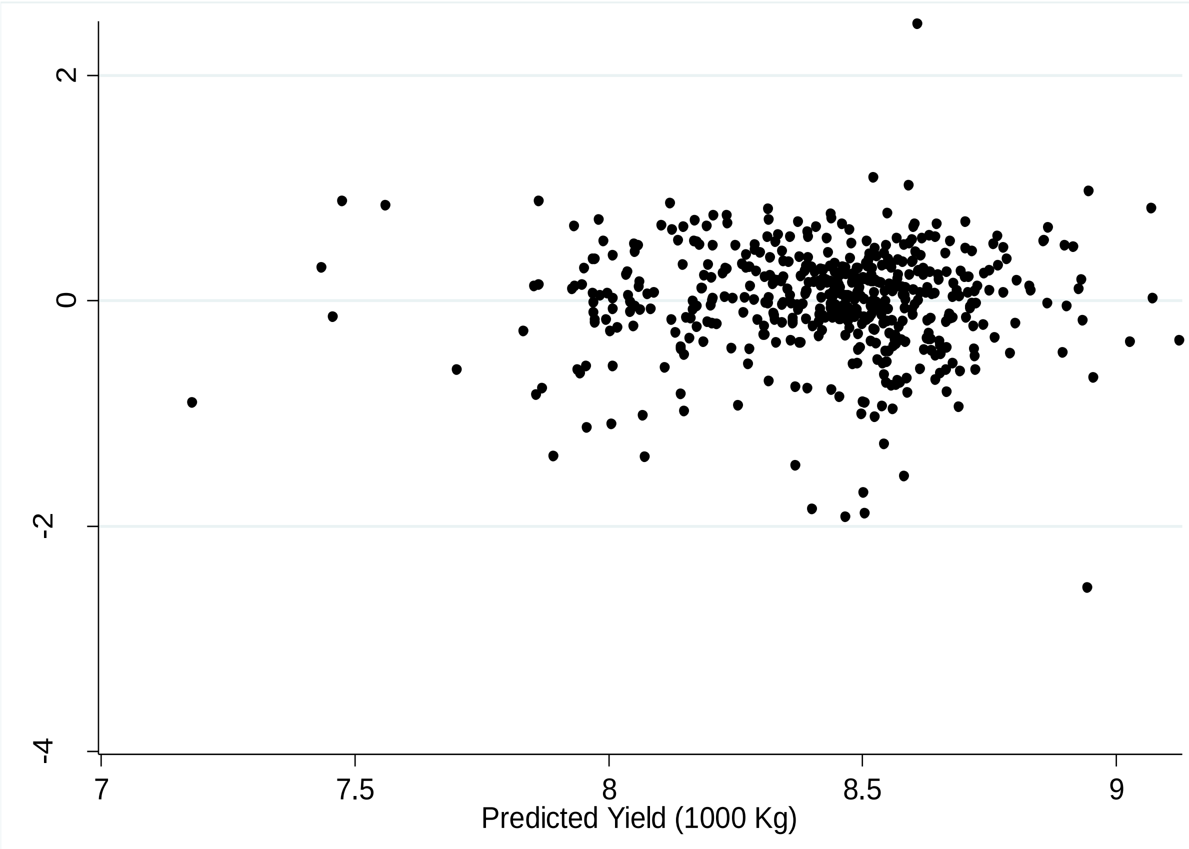

Figure A.1. Residual Plots of Yield Regression[1]

NOTE: Predicted Values at the bottom are in thousands of kilograms.
[1]The scatter plot shows that the residuals become more spread as the as yield increases. Results in Table A.10 formally test for heteroskedasticity and show that homoskedasticity can be rejected with greater than 99% confidence.

Table A.1. Full Specification Fixed Effects Estimation Results: Effect of GM Varieties on Total Labor Used (in man days), by Labor Type (e.g., Operator, Family, Hired, and All Types) [Dependent Variable = total labor time spent on all production activities]

Independent Variables	Operator Labor	Family Labor	Hired Labor	All Types
Bt	2.393*	0.0146	9.933+	12.34+
	(2.26)	(0.01)	(1.67)	(1.90)
Stacked	3.418+	-5.224	19.87+	18.07
	(1.82)	(-1.11)	(1.89)	(1.57)
HH Size	-0.525	3.034+	2.877	5.387
	(-0.79)	(1.83)	(0.77)	(1.32)
Acres Planted	-0.119	-1.016	30.30***	29.17***
	(-0.23)	(-0.78)	(10.40)	(9.16)
Seed Price	-0.187	-8.480	-25.70	-34.37
	(-0.05)	(-0.87)	(-1.17)	(-1.44)
Rolling Terrain	-1.210	-0.589	-9.349+	-11.15*
	(-1.33)	(-0.26)	(-1.83)	(-2.00)
Hilly Terrain	-1.028	1.033	2.090	2.095
	(-1.06)	(0.43)	(0.39)	(0.35)
Gravity Irrigation	0.637	-0.861	1.559	1.334
	(0.16)	(-0.09)	(0.07)	(0.06)
Pump Irrigation	1.371	-0.296	-3.206	-2.132
	(0.94)	(-0.08)	(-0.39)	(-0.24)
Owner	0.306	-6.778**	-1.475	-7.947
	(0.30)	(-2.68)	(-0.26)	(-1.28)
Off Farm: Family	20.34 (0.26)	-140.8 (-0.71)	-160.9 (-0.36)	-281.4 (-0.58)
Off Farm: Farmer	-28.86 (-0.36)	113.8 (0.56)	241.4 (0.53)	326.3 (0.66)
Constant	1.806	8.446	3.423	13.67
	(0.51)	(0.95)	(0.17)	(0.63)
R-squared	0.411	0.200	0.521	0.498
No. of Obs.	510[1]	510[1]	510[1]	510[1]

Notes: (1) Definitions of the Independent Variables are described in Table 3.2 (note (2)), (2) t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001, (3) The figures presented are the parameter estimates based on the full model specification in equation 10. In addition, the parameter estimates above is based on a Fixed Effects approach since we are aggregating man-days for all labor types (see equation 10) and not separately estimating by labor type.

Table A.2. Full Specification Fixed Effect Estimation Results: Effect of GM Varieties on Total Labor Use Across Different Production Activities [Dependent variable: total labor in man-days for All Types (aggregated for all labor types)].

Indep. Variables	------- Land Preparation Activities -------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ---------		
	Land prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App	Processing	Transport	Combined Harvest
Bt	0.186	-0.247	0.397	1.390	0.820+	-2.167+	-0.0416	-0.395	5.864	3.835**	9.699+
	(0.23)	(-0.80)	(1.09)	(1.09)	(1.84)	(-1.93)	(-0.13)	(-0.44)	(1.19)	(3.03)	(1.87)
Stacked	1.871	0.252	1.340*	2.152	0.494	-1.436	-0.136	-0.0877	11.28	3.533	14.81
	(1.33)	(0.46)	(2.08)	(0.96)	(0.63)	(-0.72)	(-0.25)	(-0.06)	(1.29)	(1.58)	(1.62)
HH Size	0.193	0.0590	0.387+	0.775	0.226	0.548	-0.277	1.549**	2.463	-0.654	1.809
	(0.39)	(0.31)	(1.69)	(0.97)	(0.81)	(0.78)	(-1.42)	(2.78)	(0.80)	(-0.82)	(0.56)
Acres	1.18**	-0.0954	0.90***	4.78***	1.461***	0.0330	0.226	4.46***	11.97***	2.929***	14.90***
	(3.05)	(-0.63)	(5.02)	(7.66)	(6.69)	(0.06)	(1.48)	(10.23)	(4.95)	(4.72)	(5.86)
Owner	-1.377+	-0.416	-0.741*	-0.295	0.453	-1.336	-0.185	-0.0472	-4.543	-0.327	-4.870
	(-1.82)	(-1.42)	(-2.13)	(-0.24)	(1.07)	(-1.25)	(-0.62)	(-0.06)	(-0.96)	(-0.27)	(-0.98)
Off Farm:	-53.83	-43.69+	18.50	-131.9	19.84	-142.6+	65.77**	-64.38	-100.9	83.40	-17.50
Family	(-0.90)	(-1.89)	(0.68)	(-1.38)	(0.59)	(-1.69)	(2.82)	(-0.96)	(-0.27)	(0.88)	(-0.05)
Off Farm:	59.77	45.48+	-15.23	134.0	-18.16	141.5+	-66.09**	66.50	123.1	-79.02	44.07
Farmer	(0.99)	(1.94)	(-0.55)	(1.38)	(-0.54)	(1.66)	(-2.80)	(0.98)	(0.33)	(-0.82)	(0.11)
2011	1.656	-0.232	-0.600	0.990	-0.112	6.446*	-1.992*	-3.265	0.181	1.085	1.266
	(0.73)	(-0.26)	(-0.57)	(0.27)	(-0.09)	(2.00)	(-2.24)	(-1.28)	(0.01)	(0.30)	(0.09)
Constant	5.296*	1.994+	-0.675	1.651	-2.857+	5.996	1.543	-4.717	7.629	0.677	8.306
	(2.00)	(1.94)	(-0.55)	(0.39)	(-1.92)	(1.60)	(1.49)	(-1.59)	(0.46)	(0.16)	(0.48)
R^2	0.545	0.203	0.562	0.409	0.320	0.274	0.651	0.433	0.214	0.317	0.287
Adj. R^2	-0.011	-0.771	0.027	-0.313	-0.511	-0.615	0.223	-0.260	-0.748	-0.519	-0.586
No. of Obs.	510	510	510	510	510	510	510	510	510	510	510

Notes: (1) Definitions of the Independent Variables are described in Table A.1 (note (2)), (2) t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001, (3) The figures presented are the parameter estimates based on the full model specification in equation 10 (Total labor use aggregated for all types), which was estimated using a Fixed Effects approach. (3) Covariates not displayed are seed price, slope and irrigation method.

Table A.3. Full Specification First Difference SUR Estimation Results: Effect of GM Varieties on Operator Labor Use Across Different Production Activities [Dependent variable: Operator labor in man-days].

Indep. Variables	------- Land Preparation Activities -------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ---------		
	Land prep.	Harrow -ing	Furrow- ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App	Processing	Transport	Combined Harvest
Bt	0.478	0.204+	0.216+	-0.0732	-0.0484	-0.0499	-0.0942**	-0.238+	2.183**	0.162	2.346**
	(1.55)	(1.92)	(1.92)	(-1.03)	(-0.24)	(-0.46)	(-3.02)	(-1.69)	(2.79)	(1.10)	(2.92)
Stacked	0.968+	0.320+	0.480*	-0.301*	-0.196	0.0176	-0.0786	-0.169	2.896*	0.213	3.109*
	(1.77)	(1.70)	(2.42)	(-2.39)	(-0.54)	(0.09)	(-1.42)	(-0.67)	(2.09)	(0.82)	(2.18)
HH Size	-0.159	0.0295	-0.0777	0.0620	-0.00872	0.0141	-0.00558	0.0304	-0.337	-0.0354	-0.372
	(-0.82)	(0.44)	(-1.10)	(1.39)	(-0.07)	(0.21)	(-0.28)	(0.34)	(-0.69)	(-0.38)	(-0.74)
Acres	-0.0606	-0.0301	-0.0185	0.00985	0.0729	-0.0109	0.00424	0.0308	-0.0928	-0.0278	-0.121
	(-0.40)	(-0.58)	(-0.34)	(0.28)	(0.73)	(-0.21)	(0.28)	(0.44)	(-0.24)	(-0.38)	(-0.31)
Owner	0.216	0.0873	0.131	0.0683	0.0868	-0.102	0.0487	0.216	-0.221	-0.185	-0.406
	(0.73)	(0.86)	(1.22)	(1.00)	(0.45)	(-0.99)	(1.63)	(1.59)	(-0.30)	(-1.31)	(-0.53)
Off Farm: Family	-4.532	-11.85	-3.824	-3.543	-1.227	-0.374	-0.736	-2.052	32.98	2.022	35.00
	(-0.20)	(-1.48)	(-0.45)	(-0.66)	(-0.08)	(-0.05)	(-0.31)	(-0.19)	(0.56)	(0.18)	(0.58)
Off Farm: Farmer	3.992	11.82	3.528	3.242	0.347	0.700	0.766	1.711	-38.46	-2.837	-41.30
	(0.17)	(1.46)	(0.41)	(0.60)	(0.02)	(0.09)	(0.32)	(0.16)	(-0.65)	(-0.25)	(-0.67)
Constant	-0.558	-0.505+	-0.158	0.126	-0.0382	-0.115	0.0383	-0.177	0.536	-0.112	0.424
	(-0.63)	(-1.65)	(-0.49)	(0.62)	(-0.07)	(-0.37)	(0.43)	(-0.44)	(0.24)	(-0.26)	(0.18)
R^2	0.130	0.166	0.138	0.263	0.266	0.229	0.237	0.271	0.153	0.146	0.179
No. of Obs.	510	510	510	510	510	510	510	510	510	510	510

Notes: (1) Definitions of the Independent Variables are described in Table A.1 (note (2)), (2) t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001, (3) The figures presented are the parameter estimates based on the full model specification in equation 21 (for operator labor), which was simultaneously estimated with equations 22 and 23 using a Fixed Effects-SUR approach (by activity).

Table A.4. First Differenced SUR Estimation Results: Effect of GM Varieties on Family Labor Use Across Different Production Activities [Dependent variable: Family labor in man-days].

Indep. Variables	------- Land Preparation Activities -------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ---------		
	Land prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App	Processing	Transport	Combined Harvest
Bt	0.175	0.0303	0.0656	-0.244	0.234	-0.461	-0.149	-0.485	0.738	0.262	0.999
	(0.37)	(0.16)	(0.35)	(-0.63)	(1.29)	(-0.58)	(-0.69)	(-1.14)	(0.55)	(0.42)	(0.60)
Stacked	-0.232	0.134	-0.338	-0.802	-0.0161	-0.722	-0.0191	-1.951**	0.0439	0.645	0.689
	(-0.28)	(0.40)	(-1.02)	(-1.16)	(-0.05)	(-0.51)	(-0.05)	(-2.60)	(0.02)	(0.58)	(0.23)
HH Size	0.0903	-0.0726	0.237*	0.907***	0.0183	1.183*	-0.260+	0.598*	0.124	-0.136	-0.0125
	(0.30)	(-0.61)	(2.02)	(3.71)	(0.16)	(2.37)	(-1.92)	(2.25)	(0.15)	(-0.35)	(-0.01)
Acres	-0.545*	-0.254**	-0.108	-0.239	0.269**	-0.885*	0.171	0.0298	-0.277	-0.0891	-0.366
	(-2.33)	(-2.73)	(-1.17)	(-1.25)	(3.01)	(-2.26)	(1.61)	(0.14)	(-0.42)	(-0.29)	(-0.45)
Owner	-0.616	-0.256	-0.448*	-0.458	-0.0560	-0.900	-0.321	-0.819*	-2.078	-1.338*	-3.417*
	(-1.35)	(-1.41)	(-2.51)	(-1.23)	(-0.32)	(-1.18)	(-1.55)	(-2.02)	(-1.63)	(-2.24)	(-2.15)
Off Farm:	-94.64**	-23.32	-33.36*	-54.64+	0.809	-51.94	74.44***	-35.22	46.12	3.336	49.45
Family	(-2.65)	(-1.64)	(-2.37)	(-1.87)	(0.06)	(-0.87)	(4.59)	(-1.11)	(0.46)	(0.07)	(0.40)
Off Farm:	91.56*	23.48	31.83*	49.16+	-0.179	47.52	-74.53***	30.20	-53.00	-5.652	-58.65
Farmer	(2.52)	(1.63)	(2.23)	(1.66)	(-0.01)	(0.78)	(-4.52)	(0.94)	(-0.52)	(-0.12)	(-0.46)
Constant	1.956	0.996+	0.528	0.756	0.931+	1.235	-2.219***	0.117	0.229	-0.186	0.0427
	(1.43)	(1.83)	(0.98)	(0.68)	(1.79)	(0.54)	(-3.57)	(0.10)	(0.06)	(-0.10)	(0.01)
R^2	0.130	0.166	0.138	0.263	0.266	0.229	0.237	0.271	0.153	0.146	0.179
No. of Obs.	510	510	510	510	510	510	510	510	510	510	510

Notes: (1) Definitions of the Independent Variables are described in Table A.1 (note (2)), (2) t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001, (3) The figures presented are the parameter estimates based on the full model specification in equation 22 (for family labor), which was simultaneously estimated with equations 21 and 23 using a Fixed Effects-SUR approach (by activity).

Table A.5. First Differenced SUR Estimation Results: Effect of GM Varieties on Hired Labor Use Across Different Production Activities [Dependent variable: Hired labor in man-days].

Indep. Variables	------- Land Preparation Activities -------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ---------		
	Land prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App	Processing	Transport	Combined Harvest
Bt	9.933+	-0.467	-0.481**	0.115	1.708	0.634*	-1.655**	0.202	0.328	2.943	3.412***
	(1.77)	(-0.96)	(-2.96)	(0.43)	(1.40)	(2.06)	(-2.72)	(1.26)	(0.40)	(0.68)	(3.80)
Stacked	19.87*	1.135	-0.202	1.199*	3.256	0.706	-0.731	-0.0387	2.032	8.338	2.675+
	(2.00)	(1.31)	(-0.70)	(2.52)	(1.51)	(1.30)	(-0.68)	(-0.14)	(1.42)	(1.09)	(1.68)
HH Size	2.877	0.261	0.102	0.228	-0.194	0.217	-0.649+	-0.0109	0.920+	2.676	-0.482
	(0.81)	(0.85)	(1.00)	(1.35)	(-0.25)	(1.12)	(-1.70)	(-0.11)	(1.81)	(0.99)	(-0.86)
Acres	30.30***	1.794***	0.189*	1.025***	5.015***	1.120***	0.929**	0.0508	4.402***	12.34***	3.046***
	(10.98)	(7.49)	(2.37)	(7.76)	(8.38)	(7.42)	(3.11)	(0.65)	(11.06)	(5.82)	(6.92)
Owner	-1.475	-0.978*	-0.248	-0.423+	0.0950	0.422	-0.333	0.0872	0.556	-2.243	1.196
	(-0.27)	(-2.10)	(-1.60)	(-1.65)	(0.08)	(1.44)	(-0.57)	(0.57)	(0.72)	(-0.54)	(1.40)
Off Farm:	-160.9	45.34	-8.522	55.69**	-73.68	20.26	-90.32*	-7.939	-27.11	-180.0	78.05
Family	(-0.38)	(1.24)	(-0.70)	(2.76)	(-0.80)	(0.88)	(-1.98)	(-0.66)	(-0.45)	(-0.56)	(1.16)
Off Farm:	241.4	-35.79	10.18	-50.59*	81.60	-18.32	93.27*	7.678	34.59	214.5	-70.53
Farmer	(0.56)	(-0.96)	(0.82)	(-2.47)	(0.88)	(-0.78)	(2.01)	(0.63)	(0.56)	(0.65)	(-1.03)
Constant	-0.130	0.257	-0.724	-0.969	0.108	-1.005	5.326**	0.189	-3.205	-0.584	1.384
	(-0.01)	(0.18)	(-1.55)	(-1.25)	(0.03)	(-1.14)	(3.05)	(0.41)	(-1.38)	(-0.05)	(0.54)
R^2	0.130	0.166	0.138	0.263	0.266	0.229	0.237	0.271	0.153	0.146	0.179
No. of Obs.	510	510	510	510	510	510	510	510	510	510	510

Notes: (1) Definitions of the Independent Variables are described in Table A.1 (note (2)), (2) t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001, (3) The figures presented are the parameter estimates based on the full model specification in equation 23 (for hired labor), which was simultaneously estimated with equations 21 and 22 using a Fixed Effects-SUR approach (by activity).

Table A.6. Three Stage Least Squares Instrumental Variables Estimation: Effect of GM Corn Adoption on Operator Labor Use on the Farm[1]

Indep. Variables	------- Land Preparation Activities -------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ---------		
	Land prep.	Plow-ing	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Processing	Transport	Combined Harvest
Bt	-0.382	-0.278	-0.205	0.101	0.0670	-0.354	0.184	-0.0556	1.621	0.349	1.970
	(-0.54)	(-0.84)	(-0.77)	(0.43)	(0.38)	(-0.64)	(0.78)	(-0.80)	(0.76)	(1.04)	(0.90)
Stacked	3.064	1.608	1.572	-0.116	0.788	3.341	-0.121	-0.162	-12.52	-0.191	-12.71
	(0.79)	(0.87)	(1.06)	(-0.09)	(0.81)	(1.10)	(-0.09)	(-0.42)	(-1.06)	(-0.10)	(-1.04)
HH Size	-0.02	-0.00363	-0.01	-0.0008	-0.003	0.009	0.02	0.002	0.03	0.01	0.05
	(-0.41)	(-0.17)	(-0.81)	(-0.05)	(-0.25)	(0.25)	(1.48)	(0.49)	(0.25)	(0.67)	(0.35)
Acres	0.0815	0.0374	0.0144	0.0296	0.0512	0.192+	-0.0145	-0.00387	-0.141	0.0600	-0.0806
	(0.55)	(0.54)	(0.26)	(0.60)	(1.39)	(1.66)	(-0.29)	(-0.26)	(-0.31)	(0.85)	(-0.17)
Owner	0.365	0.111	0.203	0.0509	0.0778	0.259	-0.0544	0.00329	-1.089	-0.284	-1.372
	(0.99)	(0.64)	(1.45)	(0.42)	(0.85)	(0.90)	(-0.44)	(0.09)	(-0.98)	(-1.61)	(-1.19)
Off Farm: Family	-0.396	0.0791	0.0481	-0.523	-0.0962	0.553	0.108	-0.0588	-6.101	-0.274	-6.375
	(-0.23)	(0.10)	(0.07)	(-0.91)	(-0.22)	(0.41)	(0.19)	(-0.34)	(-1.16)	(-0.33)	(-1.17)
Off Farm: Farmer	-0.517	-0.376	0.245	-0.386	0.103	-0.546	-0.818	-0.0669	-5.514	-1.528	-7.042
	(-0.24)	(-0.37)	(0.30)	(-0.54)	(0.19)	(-0.32)	(-1.12)	(-0.31)	(-0.84)	(-1.47)	(-1.04)
2011	-3.135	-1.459	-1.813	0.137	-0.620	-3.100	0.240	0.0768	11.33	0.359	11.69
	(-0.87)	(-0.86)	(-1.32)	(0.11)	(-0.69)	(-1.10)	(0.20)	(0.22)	(1.04)	(0.21)	(1.03)
Constant	0.865	0.307	0.628+	-0.0696	-0.00899	0.117	-0.171	0.0204	-0.468	0.124	-0.344
	(1.00)	(0.75)	(1.90)	(-0.24)	(-0.04)	(0.17)	(-0.59)	(0.24)	(-0.18)	(0.30)	(-0.13)
R^2	-0.010	-0.125	-0.219	0.139	0.065	-0.133	0.206	0.145	-0.367	0.079	-0.338
No. of Obs.	503	503	503	503	503	503	503	503	503	503	503

[1]Table A.6 shows improved conformance (but not significantly so) of farm operator behavior with prior interpretations of the behavior of Bt vs Stacked on the distribution of yield. The effect of Bt occurs predominantly at harvest time while the effect of Stacked is seen primarily in the pre-harvest period.
t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A.7. First Difference and Farm Wealth Interaction: Effect of Changes in Wealth on the Marginal Impact of GM Corn Adoption on Farm Operator[1]

Indep. Variables	------- Land Preparation Activities -------					-------- Pest Mgt. Activities --------			---------- Harvest Activities ---------		
	Land prep.	Plow-ing	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Processing	Transport	Combined Harvest
Bt	0.342	-0.0135	0.158	0.197	-0.0790	-0.0860	-0.121	-0.111**	2.124*	0.209	2.333*
	(0.90)	(-0.08)	(1.18)	(1.40)	(-0.91)	(-0.34)	(-0.90)	(-2.89)	(2.16)	(1.14)	(2.31)
Stacked	1.015+	0.182	0.342+	0.491*	-0.313*	-0.192	-0.0579	-0.0871	3.005*	0.241	3.246*
	(1.78)	(0.76)	(1.71)	(2.34)	(-2.42)	(-0.50)	(-0.29)	(-1.51)	(2.04)	(0.88)	(2.15)
Bt X Wealth	7.487	4.055	2.855	0.577	-0.460	3.634	7.122	1.090	34.76	-6.845	27.91
	(0.41)	(0.54)	(0.45)	(0.09)	(-0.11)	(0.30)	(1.12)	(0.60)	(0.75)	(-0.79)	(0.58)
St X Wealth	0.123	1.654	-0.551	-0.980	-1.276	1.373	7.576	0.431	42.25	-8.128	34.12
	(0.01)	(0.22)	(-0.09)	(-0.15)	(-0.31)	(0.11)	(1.17)	(0.23)	(0.90)	(-0.92)	(0.70)
Wealth[2]	-1.195	-1.414	-0.638	0.857	2.033	0.428	-7.380	-0.967	-24.31	12.10	-12.22
	(-0.07)	(-0.19)	(-0.10)	(0.13)	(0.51)	(0.04)	(-1.18)	(-0.54)	(-0.53)	(1.42)	(-0.26)
HH Size	-0.16	-0.076	-0.0036	-0.084	0.058	-0.011	0.031	-0.0043	-0.32	-0.022	-0.34
	(-0.84)	(-0.93)	(-0.05)	(-1.17)	(1.32)	(-0.09)	(0.46)	(-0.22)	(-0.64)	(-0.23)	(-0.66)
Acres	-6.510	-3.359	-1.792	-1.359	1.266	8.093	-1.084	0.481	-14.39	-3.678	-18.07
	(-0.42)	(-0.52)	(-0.33)	(-0.24)	(0.36)	(0.78)	(-0.20)	(0.31)	(-0.36)	(-0.50)	(-0.44)
Owner	0.106	-0.0617	0.0603	0.108	0.0581	0.156	-0.113	0.0572+	-0.349	-0.212	-0.561
	(0.32)	(-0.45)	(0.53)	(0.89)	(0.79)	(0.71)	(-0.98)	(1.73)	(-0.42)	(-1.35)	(-0.65)
Constant	-0.625	0.0353	-0.496	-0.164	0.150	-0.0870	-0.121	0.0563	0.369	-0.138	0.232
	(-0.69)	(0.09)	(-1.56)	(-0.49)	(0.73)	(-0.14)	(-0.38)	(0.62)	(0.16)	(-0.32)	(0.10)
R^2	0.148	0.148	0.180	0.142	0.275	0.270	0.251	0.262	0.162	0.170	0.188
No. of Obs.[3]	474	474	474	474	474	474	474	474	474	474	474

[1]Results test Corollaries 2 and 3 which predicts the effect of changes in wealth (coefficient of risk aversion: see Corollary 2 and 3). If Bt Corn is primarily mean yield increasing and variance reducing, then the farm operator conforms to DARA behavior (see Figure 3.1).
[2]Farm wealth is calculated as the monetary value of farm assets which include land and fixed capital such as hand tractors and water pumps.
[3]237 First Differenced observations from panel of 474 observations. 18 farms with missing asset values were dropped.
t-statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A.8. First Differenced with Interaction: Impact of Changes in Wealth on the Marginal Effect of GM Adoption on Farm Operator On-Farm Labor Time[1]

Indep. Variables	------- Land Preparation Activities -------					------- Pest Mgt. Activities -------			---------- Harvest Activities ---------		
	Land prep.	Plow-ing	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Processing	Transport	Combined Harvest
Bt	0.105	-0.181	0.252	0.0333	0.124	-1.700	-1.544+	-0.0347	-6.862	-0.917	-7.780
	(0.04)	(-0.17)	(0.28)	(0.04)	(0.21)	(-0.99)	(-1.70)	(-0.13)	(-1.03)	(-0.74)	(-1.13)
Stacked	4.936*	1.358	1.717*	1.861*	0.0713	-0.679	-1.460+	0.0735	-2.075	0.984	-1.091
	(2.24)	(1.45)	(2.22)	(2.30)	(0.14)	(-0.46)	(-1.86)	(0.32)	(-0.36)	(0.92)	(-0.18)
Bt X Wealth	0.0207	0.0153	-0.00715	0.0125	-0.0188	0.140	0.135+	-0.00633	0.809	0.0873	0.896
	(0.09)	(0.16)	(-0.09)	(0.15)	(-0.36)	(0.93)	(1.68)	(-0.27)	(1.37)	(0.80)	(1.48)
St X Wealth	-0.383+	-0.114	-0.134+	-0.135+	-0.0380	0.0377	0.135+	-0.0166	0.470	-0.0820	0.388
	(-1.92)	(-1.34)	(-1.92)	(-1.84)	(-0.82)	(0.28)	(1.90)	(-0.79)	(0.90)	(-0.85)	(0.72)
Wealth[2]	0.205	0.0720	0.0618	0.0715	0.0306	0.111	-0.166*	0.0136	-0.289	0.123	-0.166
	(0.96)	(0.79)	(0.83)	(0.91)	(0.62)	(0.77)	(-2.19)	(0.61)	(-0.52)	(1.18)	(-0.29)
HH Size	-0.175	-0.0841	-0.00482	-0.0858	0.0565	-0.0320	0.0346	-0.00121	-0.360	-0.0418	-0.402
	(-0.92)	(-1.04)	(-0.07)	(-1.23)	(1.28)	(-0.25)	(0.51)	(-0.06)	(-0.72)	(-0.45)	(-0.78)
Acres	-6.237	-3.953	-1.641	-0.643	1.796	7.925	-1.709	1.040	-13.39	-3.650	-17.04
	(-0.41)	(-0.62)	(-0.31)	(-0.12)	(0.52)	(0.79)	(-0.32)	(0.65)	(-0.34)	(-0.50)	(-0.42)
Owner	0.109	-0.0521	0.0481	0.113	0.0586	0.180	-0.112	0.0421	-0.203	-0.161	-0.365
	(0.35)	(-0.39)	(0.44)	(0.98)	(0.80)	(0.85)	(-1.00)	(1.27)	(-0.25)	(-1.05)	(-0.43)
Constant	-0.479	0.177	-0.492	-0.164	0.0907	0.198	-0.167	-0.0179	0.486	0.0720	0.558
	(-0.55)	(0.48)	(-1.61)	(-0.51)	(0.45)	(0.34)	(-0.54)	(-0.19)	(0.21)	(0.17)	(0.24)
R^2	0.178	0.142	0.207	0.177	0.267	0.291	0.260	0.219	0.164	0.174	0.191
No. of Obs.[2]	474	474	474	474	474	474	474	474	474	474	474

[1]Results to test the risk behavior of farmers as predicted and Corollaries 2 and 3. Wealth is calculated as the log of the sum of the monetary value of farm assets which include the value of land and fixed farm capital such as hand tractors and water pumps.
[2]237 First Differenced observations from panel of 474 observations. 18 farms with missing asset values were dropped.
t-statistics in parentheses: + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A.9. Effect of Bt and Stacked adoption on Yield, Variance and Skewness

	Just-Pope Specification			Maximum Likelihood	
Independent Variables	Yield	Variance	Skewness	Yield	Variance
Bt dummy	0.157**	-0.0704	-0.0681	0.1705***	0.1564
	(0.0732)	(0.0648)	(0.117)	(0.0554)	(0.195)
Stacked dummy	-0.0107	-0.234**	0.105	0.1198	-0.5182**
	(0.141)	(0.105)	(0.19)	(0.163)	(0.1954)
Herbicide (L/Ha)	0.0295	0.0315	0.0682	0.00984	0.1685**
	(0.0321)	(0.0307)	(0.0555)	(0.0281)	(0.0678)
Insecticide (Kg/Ha)	-0.180***	0.0423	0.0338	-0.0602	0.3821**
	(0.0512)	(0.0458)	(0.083)	(0.0564)	(0.174)
Fertilizer (Kg/Ha)	0.00427	-0.0733	0.0498	0.0198	-0.6587***
	(0.0471)	(0.0529)	(0.0959)	(0.0371)	(0.158)
Labor	0.120**	-0.0385	0.0563	0.0952**	-0.2599**
(Man Days/Ha)	(0.0539)	(0.0425)	(0.077)	(0.0386)	(0.116)
Seed Quantity	0.313***	0.029	-0.0768	0.3588***	0.1962
(Kg/Ha)	(0.0748)	(0.0752)	(0.136)	(0.590)	(0.263)
Irrigation:		-0.423*	0.233		-2.8260***
Gravity dummy		(0.247)	(0.448)		(0.851)
Irrigation:		0.0677	-0.0238		0.3037
Pump dummy		(0.102)	(0.185)		(0.292)
Terrain:		0.0264	-0.0389		0.0865
Rolling		(0.0654)	(0.119)		(0.170)
Terrain:		0.0295	0.0282		0.2471
Hilly/Mountainous		(0.0684)	(0.124)		(0.188)
Household		0.0252	-0.0275		-0.0386
Size		(0.0451)	(0.0817)		(0.0402)
Planted Area		0.0844*	-0.121		0.4523***
		(0.0508)	(0.0921)		(0.213)
Constant	6.890***	0.137*	-0.133	6.678***	0.587**
	(0.269)	(0.0803)	(0.145)	(0.294)	(0.209)
R^2	0.437	0.046	0.046	0.351	0.351
Observations	510	510	510	510	510

Notes: (1) The dependent variable in the regressions above is Yield (in kg/ha).
(2) * p<0.10, ** p<0.05, *** p<0.01.

Table A.10. White General Test for Heteroskedasticity on Farm Yield

Source	Chi2	df	p
Heteroskedasticity	65.38	39	0.0051[1]
Skewness	12.64	8	0.1249
Kurtosis	5.11	1	0.0238
Total	83.13	48	0.0012

[1]Test shows that the null hypothesis of the data having uniform variance being rejected with greater than 99% confidence.

Table A.11. Test of Independence of Operator, Family and Hired Labor

	Operator	Family	Hired
Operator	1		
Family	0.3032	1	
Hired	0.0356	-0.1083	1

Breusch-Pagan test: chi(3) = 26.751, Pr = 0.0000[1]

Test rejects independence of the three labor equations with greater than 99% confidence.

Table A.12. Probit Estimation on Determinants of Being Included in the Second Year Sample

Indep. Vars	Probability of Remaining
Farmer Age	0.0308***
	(5.53)
Female	-0.507*
	(-2.44)
Farm Ownership	0.761**
	(2.91)
Corn Acreage	0.514*
	(2.55)
Labor Hired	-0.00888**
	(-2.78)
Corn Production	-0.0000505
	(-1.41)
Isabela	1.568***
	(7.07)
Planted Bt	-0.233
	(-1.40)
Household Size	0.116**
	(2.69)
Gravity Irrigation	-0.785*
	(-2.54)
Pump Irrigation	0.216
	(0.68)
Years Farming Corn	-0.0109
	(-1.56)
Constant	-2.836***
	(-6.35)
Observations	447

t statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A.13. Weighted Fixed Effects Regression of Aggregate Labor Man Days for Operator, Family and Hired Labor

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.0687	-0.167	0.330	2.005	0.787*	-3.810*	-0.198	-1.041	0.868	1.781	2.649
	(0.09)	(-0.49)	(0.76)	(1.34)	(2.40)	(-1.98)	(-0.57)	(-1.13)	(0.18)	(1.28)	(0.47)
Stacked	2.222+	0.201	1.759*	3.436	0.376	-4.657	-0.265	-0.424	6.885	1.155	8.040
	(1.72)	(0.30)	(2.51)	(1.55)	(0.76)	(-0.93)	(-0.40)	(-0.31)	(0.96)	(0.57)	(0.96)
Household Size	0.708	0.347	0.492+	0.838	0.165	0.0390	-0.485+	1.748**	2.850	-0.778	2.072
	(1.44)	(1.31)	(1.70)	(1.37)	(1.00)	(0.03)	(-1.96)	(2.99)	(1.41)	(-1.33)	(0.97)
Corn Acreage	1.634*	0.0938	0.970*	4.297***	0.943**	1.105	0.243	3.299***	10.78***	1.768*	12.55***
	(2.49)	(0.36)	(2.33)	(4.16)	(2.68)	(0.99)	(1.60)	(3.37)	(4.41)	(2.09)	(4.42)
Owner	-1.732*	-0.490	-0.871+	-0.630	0.553+	-1.491	-0.388	-0.649	-5.148*	-0.144	-5.291
	(-2.36)	(-1.56)	(-1.95)	(-0.60)	(1.71)	(-0.87)	(-1.18)	(-0.78)	(-2.00)	(-0.11)	(-1.62)
Family Off Farm	-33.07	-42.77	39.95	-142.8+	20.86	-100.1	73.48**	-82.64	-155.4	28.77	-126.6
Income (PhP)	(-0.26)	(-0.95)	(0.46)	(-1.77)	(0.82)	(-1.02)	(2.85)	(-0.78)	(-0.41)	(0.43)	(-0.36)
Farmer Off Farm	44.24	44.88	-31.25	157.3+	-17.75	85.29	-72.54**	95.11	182.8	-20.78	162.0
Income (PhP)	(0.35)	(0.99)	(-0.36)	(1.89)	(-0.67)	(0.84)	(-2.75)	(0.88)	(0.48)	(-0.31)	(0.46)
Constant	1.921	0.689	-1.812	1.757	-2.300*	4.953	2.492+	-4.019	4.288	3.217	7.505
	(0.43)	(0.42)	(-0.61)	(0.48)	(-2.02)	(1.05)	(1.90)	(-0.92)	(0.31)	(0.82)	(0.55)
R^2	0.601	0.209	0.583	0.491	0.255	0.382	0.698	0.437	0.299	0.301	0.358
Adj. R^2	0.579	0.167	0.560	0.464	0.215	0.349	0.682	0.407	0.262	0.263	0.324
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A.14. Weighted Fixed Effects Regression of Operator On-Farm Labor Man Days

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities -------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.286	0.149	0.131	-0.0713	-0.0737	-0.00376	-0.0697*	-0.204+	1.677	0.0861	1.763
	(1.10)	(1.58)	(1.30)	(-1.15)	(-0.62)	(-0.03)	(-2.05)	(-1.68)	(1.52)	(0.69)	(1.58)
Stacked	0.611	0.210	0.297+	-0.265+	-0.253	0.00772	-0.0523	-0.195	2.267	0.163	2.430+
	(1.39)	(1.35)	(1.75)	(-1.92)	(-1.62)	(0.04)	(-1.08)	(-1.12)	(1.59)	(0.75)	(1.66)
Household Size	-0.113	0.0409	-0.0602+	0.0420	-0.0323	0.0118	-0.00599	0.0243	-0.268	-0.0456	-0.314
	(-1.42)	(1.20)	(-1.91)	(1.10)	(-0.57)	(0.77)	(-0.76)	(0.36)	(-1.28)	(-0.88)	(-1.34)
Corn Acreage	-0.0759	-0.0178	-0.0169	0.00817	0.0366	-0.0124	0.00247	0.0113	0.00679	-0.0339	-0.0271
	(-1.12)	(-0.58)	(-0.71)	(0.35)	(0.50)	(-0.96)	(0.35)	(0.25)	(0.06)	(-1.00)	(-0.20)
Owner	0.162	0.0617	0.0900	0.0729	0.0992	-0.0865	0.0372+	0.198*	-0.166	-0.113	-0.279
	(0.94)	(0.94)	(1.50)	(1.37)	(1.53)	(-0.65)	(1.94)	(2.45)	(-0.52)	(-0.61)	(-0.68)
Family Off Farm	0.500	-7.282	-1.608	-2.151	-0.573	-0.619	-0.356	-2.450	26.06	3.585	29.65
Income (PhP)	(0.06)	(-1.56)	(-0.56)	(-1.09)	(-0.15)	(-0.29)	(-0.58)	(-0.58)	(1.13)	(1.02)	(1.20)
Farmer Off Farm	-0.0250	7.408	1.300	2.146	0.0649	0.727	0.346	2.380	-29.17	-4.324	-33.49
Income (PhP)	(-0.00)	(1.54)	(0.45)	(0.98)	(0.02)	(0.33)	(0.54)	(0.49)	(-1.22)	(-1.17)	(-1.31)
Constant	0.501	-0.00848	0.244	-0.266	-0.144	0.0228	0.0628	-0.245	0.908	0.243	1.151
	(1.05)	(-0.04)	(1.37)	(-1.44)	(-0.46)	(0.20)	(1.33)	(-0.72)	(1.06)	(1.05)	(1.18)
R^2	0.136	0.188	0.137	0.351	0.363	0.220	0.203	0.434	0.204	0.178	0.234
Adj. R^2	0.089	0.144	0.091	0.316	0.329	0.178	0.160	0.404	0.161	0.133	0.193
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A.15. Weighted Fixed Effects Regression of Family On-Farm Labor Man Days

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.549	0.297	0.0166	-0.400	0.279	-1.014	-0.196	-0.560	-0.0957	0.0260	-0.0697
	(1.03)	(1.16)	(0.09)	(-0.87)	(1.34)	(-0.70)	(-0.61)	(-1.34)	(-0.05)	(0.05)	(-0.03)
Stacked	-0.243	0.173	-0.375	-0.973	0.0817	-3.217	0.0479	-1.960*	-1.098	0.152	-0.946
	(-0.25)	(0.32)	(-0.85)	(-0.96)	(0.25)	(-0.75)	(0.08)	(-2.07)	(-0.43)	(0.21)	(-0.34)
Household Size	0.257	0.100	0.168	0.790*	0.0168	0.965	-0.451+	0.637	0.206	-0.122	0.0837
	(0.72)	(0.51)	(1.03)	(2.14)	(0.16)	(1.27)	(-1.87)	(1.59)	(0.44)	(-1.04)	(0.16)
Corn Acreage	-0.369	-0.176	-0.133	-0.310+	0.210	-0.928*	0.251	-0.0646	0.0385	-0.123	-0.0846
	(-1.39)	(-1.41)	(-1.43)	(-1.78)	(1.60)	(-2.24)	(1.54)	(-0.36)	(0.10)	(-1.03)	(-0.20)
Owner	-0.747	-0.243	-0.440*	-0.392	0.0553	-1.181	-0.488	-0.912*	-2.142*	-0.980	-3.122+
	(-1.47)	(-1.17)	(-2.04)	(-0.87)	(0.37)	(-0.78)	(-1.63)	(-2.02)	(-2.23)	(-1.09)	(-1.82)
Family Off Farm	-94.93*	-29.66**	-30.10*	-51.75+	0.838	-4.478	82.42**	-38.23	48.98	5.366	54.35
Income (PhP)	(-2.42)	(-2.77)	(-2.21)	(-1.89)	(0.06)	(-0.05)	(2.94)	(-1.16)	(1.12)	(0.61)	(1.18)
Farmer Off Farm	93.30*	29.20**	29.29*	47.37+	-1.037	-0.158	-81.02**	33.72	-54.85	-7.053	-61.90
Income (PhP)	(2.34)	(2.68)	(2.13)	(1.69)	(-0.07)	(-0.00)	(-2.85)	(1.00)	(-1.21)	(-0.74)	(-1.31)
Constant	4.145*	0.949	1.277+	-0.0675	-0.498	0.0913	1.512	0.652	2.839	1.087	3.926+
	(2.53)	(1.22)	(1.73)	(-0.04)	(-0.84)	(0.03)	(1.26)	(0.39)	(1.46)	(1.59)	(1.71)
R^2	0.504	0.241	0.478	0.319	0.166	0.245	0.731	0.290	0.068	0.074	0.067
Adj. R^2	0.477	0.201	0.449	0.282	0.122	0.204	0.717	0.252	0.018	0.024	0.016
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A.16. Weighted Fixed Effects Regression of Hired On-Farm Labor Man Days

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	-0.766	-0.613**	0.182	2.476+	0.582*	-2.792*	0.0678	-0.277	-0.713	1.669	0.956
	(-1.26)	(-3.02)	(0.43)	(1.73)	(2.26)	(-2.37)	(0.38)	(-0.31)	(-0.18)	(1.33)	(0.20)
Stacked	1.854*	-0.183	1.836**	4.674*	0.548	-1.448	-0.261	1.731	5.717	0.839	6.556
	(2.10)	(-0.54)	(3.02)	(2.10)	(1.43)	(-0.79)	(-0.92)	(1.43)	(0.95)	(0.46)	(0.91)
Household Size	0.564	0.206	0.384	0.00642	0.181	-0.938	-0.0276	1.087*	2.913	-0.610	2.302
	(1.41)	(1.52)	(1.48)	(0.01)	(1.39)	(-1.60)	(-0.28)	(2.12)	(1.50)	(-1.08)	(1.13)
Corn Acreage	2.078**	0.288	1.121*	4.598***	0.697*	2.046*	-0.0107	3.352**	10.73***	1.925*	12.66***
	(2.90)	(1.43)	(2.45)	(4.36)	(2.58)	(2.09)	(-0.14)	(3.16)	(4.49)	(2.33)	(4.51)
Owner	-1.148+	-0.309	-0.521	-0.311	0.398	-0.223	0.0623	0.0645	-2.840	0.949	-1.890
	(-1.81)	(-1.55)	(-1.21)	(-0.31)	(1.53)	(-0.27)	(0.43)	(0.08)	(-1.19)	(1.46)	(-0.71)
Family Off Farm	61.36	-5.823	71.66	-88.92	20.60	-94.97+	-8.580	-41.95	-230.4	19.82	-210.6
Income (PhP)	(0.42)	(-0.14)	(0.77)	(-0.91)	(1.31)	(-1.89)	(-1.38)	(-0.33)	(-0.65)	(0.29)	(-0.65)
Farmer Off Farm	-49.03	8.274	-61.83	107.8	-16.78	84.72	8.133	59.01	266.8	-9.408	257.4
Income (PhP)	(-0.33)	(0.20)	(-0.66)	(1.08)	(-1.03)	(1.52)	(1.25)	(0.46)	(0.75)	(-0.14)	(0.79)
Constant	-2.725	-0.252	-3.333	2.090	-1.658+	4.839+	0.918+	-4.427	0.541	1.886	2.428
	(-0.59)	(-0.20)	(-1.10)	(0.54)	(-1.94)	(1.69)	(1.80)	(-0.96)	(0.04)	(0.50)	(0.18)
R^2	0.592	0.239	0.541	0.446	0.218	0.518	0.424	0.396	0.348	0.415	0.413
Adj. R^2	0.570	0.198	0.516	0.416	0.176	0.492	0.393	0.363	0.312	0.383	0.382
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A.17. Fixed Effects Regression of Aggregate Labor Man Days for Operator, Family and Hired Labor: Clustered Standard Errors

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.186	-0.247	0.397	1.390	0.820+	-2.167+	-0.0416	-0.395	5.864	3.835*	9.699
	(0.19)	(-0.78)	(1.09)	(1.28)	(2.02)	(-1.88)	(-0.11)	(-0.51)	(0.86)	(2.44)	(1.29)
Stacked	1.871	0.252	1.340**	2.152	0.494	-1.436	-0.136	-0.0877	11.28	3.533*	14.81+
	(1.53)	(0.43)	(3.26)	(1.46)	(0.87)	(-0.89)	(-0.26)	(-0.06)	(1.48)	(2.39)	(1.92)
Household Size	0.193	0.0590	0.387*	0.775	0.226*	0.548	-0.277+	1.549***	2.463*	-0.654	1.809
	(0.74)	(0.40)	(2.32)	(0.97)	(2.92)	(0.44)	(-1.98)	(4.60)	(2.16)	(-1.56)	(1.58)
Corn Acreage	1.188	-0.0954	0.898*	4.786***	1.461+	0.0330	0.226+	4.463**	11.97***	2.929+	14.90***
	(1.52)	(-0.38)	(2.41)	(5.14)	(2.05)	(0.05)	(1.78)	(3.19)	(11.08)	(2.06)	(8.83)
Owner	-1.377	-0.416	-0.741+	-0.295	0.453	-1.336	-0.185	-0.0472	-4.543+	-0.327	-4.870
	(-1.74)	(-1.28)	(-2.08)	(-0.55)	(0.91)	(-0.94)	(-0.77)	(-0.04)	(-2.08)	(-0.16)	(-1.34)
Family Off Farm	-53.83	-43.69	18.50	-131.9*	19.84	-142.6*	65.77***	-64.38	-100.9	83.40	-17.50
Income (PhP)	(-0.38)	(-0.84)	(0.21)	(-2.25)	(0.38)	(-2.53)	(8.83)	(-1.19)	(-0.31)	(1.09)	(-0.06)
Farmer Off Farm	59.77	45.48	-15.23	134.0*	-18.16	141.5*	-66.09***	66.50	123.1	-79.02	44.07
Income (PhP)	(0.42)	(0.88)	(-0.18)	(2.23)	(-0.36)	(2.69)	(-7.52)	(1.20)	(0.38)	(-1.03)	(0.16)
Constant	5.296	1.994	-0.675	1.651	-2.857	5.996	1.543+	-4.717	7.629	0.677	8.306
	(1.38)	(1.37)	(-0.28)	(0.37)	(-1.69)	(1.51)	(1.97)	(-1.20)	(0.80)	(0.18)	(1.09)
R^2	0.545	0.203	0.562	0.409	0.320	0.274	0.651	0.433	0.214	0.317	0.287
Adj. R^2	0.521	0.160	0.539	0.377	0.284	0.234	0.632	0.403	0.171	0.280	0.248
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard errors clustered at the Barangay level.

Table A.18. Fixed Effects Regression of Operator On-Farm Labor Man Days: Clustered Standard Errors

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities -------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.478	0.204	0.216	-0.0732	-0.0484	-0.0499	-0.0942	-0.238	2.183	0.162	2.346
	(0.75)	(1.01)	(0.96)	(-0.95)	(-0.44)	(-0.28)	(-1.53)	(-1.70)	(1.41)	(0.90)	(1.42)
Stacked	0.968	0.320	0.480	-0.301	-0.196	0.0176	-0.0786	-0.169	2.896	0.213	3.109
	(0.83)	(0.82)	(1.16)	(-1.36)	(-0.84)	(0.07)	(-1.01)	(-0.65)	(1.32)	(0.79)	(1.30)
Household Size	-0.159	0.0295	-0.0777	0.0620	-0.00872	0.0141	-0.00558	0.0304	-0.337	-0.0354	-0.372
	(-1.20)	(0.73)	(-1.38)	(1.08)	(-0.21)	(0.66)	(-0.93)	(0.89)	(-0.69)	(-0.51)	(-0.69)
Corn Acreage	-0.0606	-0.0301	-0.0185	0.00985	0.0729	-0.0109	0.00424	0.0308	-0.0928	-0.0278	-0.121
	(-0.80)	(-0.77)	(-0.56)	(0.50)	(1.15)	(-0.72)	(0.42)	(0.90)	(-0.56)	(-0.58)	(-0.67)
Owner	0.216+	0.0873	0.131	0.0683	0.0868	-0.102	0.0487+	0.216	-0.221	-0.185	-0.406
	(1.99)	(1.56)	(1.53)	(1.07)	(1.14)	(-0.64)	(1.80)	(1.70)	(-0.86)	(-0.75)	(-1.00)
Family Off Farm	-4.532	-11.85	-3.824	-3.543	-1.227	-0.374	-0.736	-2.052	32.98	2.022	35.00
Income (PhP)	(-0.24)	(-1.57)	(-0.65)	(-1.23)	(-0.41)	(-0.11)	(-0.62)	(-0.52)	(1.35)	(0.72)	(1.34)
Farmer Off Farm	3.992	11.82	3.528	3.242	0.347	0.700	0.766	1.711	-38.46	-2.837	-41.30
Income (PhP)	(0.22)	(1.62)	(0.61)	(1.07)	(0.11)	(0.19)	(0.63)	(0.39)	(-1.51)	(-0.85)	(-1.51)
Constant	0.711	0.0840	0.342	-0.328	-0.289	0.00808	0.0747*	-0.307	1.333	0.222	1.555
	(1.02)	(0.34)	(1.12)	(-1.49)	(-0.97)	(0.07)	(2.47)	(-1.34)	(0.70)	(0.63)	(0.72)
R^2	0.152	0.177	0.152	0.370	0.370	0.242	0.239	0.443	0.219	0.163	0.249
Adj. R^2	0.106	0.133	0.107	0.336	0.337	0.201	0.198	0.413	0.177	0.118	0.208
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors clustered at the Barangay level.

Table A.19. Fixed Effects Regression of Family On-Farm Labor Man Days: Clustered Standard Errors

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	0.175	0.0303	0.0656	-0.244	0.234	-0.461	-0.149	-0.485	0.738	0.262	0.999
	(0.29)	(0.13)	(0.41)	(-0.94)	(1.04)	(-1.07)	(-0.79)	(-1.09)	(0.32)	(0.45)	(0.43)
Stacked	-0.232	0.134	-0.338	-0.802	-0.0161	-0.722	-0.0191	-1.951	0.0439	0.645	0.689
	(-0.24)	(0.28)	(-0.78)	(-1.04)	(-0.04)	(-1.41)	(-0.06)	(-1.68)	(0.02)	(0.64)	(0.23)
Household Size	0.0903	-0.0726	0.237	0.907+	0.0183	1.183	-0.260*	0.598+	0.124	-0.136	-0.0125
	(0.41)	(-0.54)	(1.49)	(1.79)	(0.15)	(1.31)	(-2.44)	(1.80)	(0.15)	(-1.05)	(-0.01)
Corn Acreage	-0.545+	-0.254**	-0.108	-0.239	0.269**	-0.885+	0.171	0.0298	-0.277	-0.0891	-0.366
	(-2.04)	(-4.20)	(-0.75)	(-1.30)	(3.36)	(-1.86)	(1.77)	(0.10)	(-0.46)	(-0.84)	(-0.61)
Owner	-0.616+	-0.256	-0.448*	-0.458+	-0.0560	-0.900	-0.321	-0.819	-2.078	-1.338	-3.417
	(-2.12)	(-1.62)	(-2.43)	(-2.00)	(-0.23)	(-0.72)	(-1.48)	(-1.25)	(-1.51)	(-0.92)	(-1.27)
Family Off Farm Income (PhP)	-94.64**	-23.32***	-33.36**	-54.64*	0.809	-51.94	74.44***	-35.22+	46.12	3.336	49.45
	(-3.16)	(-4.70)	(-3.86)	(-2.80)	(0.05)	(-1.51)	(12.40)	(-1.84)	(1.05)	(0.37)	(1.29)
Farmer Off Farm Income (PhP)	91.56**	23.48***	31.83**	49.16*	-0.179	47.52	-74.53***	30.20	-53.00	-5.652	-58.65
	(3.06)	(4.96)	(3.74)	(2.44)	(-0.01)	(1.51)	(-12.07)	(1.64)	(-1.17)	(-0.64)	(-1.46)
Constant	5.012*	1.628*	1.159	-0.551	-0.393	-0.308	0.597	0.483	3.329	1.026	4.354
	(2.54)	(2.97)	(1.27)	(-0.24)	(-0.42)	(-0.15)	(1.33)	(0.32)	(0.82)	(0.93)	(0.90)
R^2	0.470	0.210	0.449	0.323	0.186	0.233	0.696	0.264	0.060	0.093	0.065
Adj. R^2	0.441	0.168	0.419	0.286	0.142	0.191	0.680	0.224	0.009	0.044	0.015
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors clustered at the Barangay level.

Table A.20. Fixed Effects Regression of Hired On-Farm Labor Man Days: Clustered Standard Errors

Indep. Variables	------- Land Preparation Activities ------				-------- Pest Mgt. and Fert. Activities --------				---------- Harvest Activities ------		
	Land Prep.	Harrow-ing	Furrow-ing	Planting	Herbicide App.	Weeding	Pesticide App.	Fertilizer App.	Processing	Transport	Combined Harvest
Bt	-0.467	-0.481**	0.115	1.708	0.634*	-1.655*	0.202	0.328	2.943	3.412*	6.354
	(-0.83)	(-3.81)	(0.31)	(1.75)	(2.34)	(-2.20)	(0.99)	(0.53)	(0.61)	(2.53)	(1.12)
Stacked	1.135	-0.202	1.199+	3.256*	0.706+	-0.731	-0.0387	2.032**	8.338	2.675+	11.01+
	(1.31)	(-1.06)	(1.87)	(2.28)	(2.07)	(-0.64)	(-0.17)	(3.16)	(1.44)	(2.12)	(1.81)
Household Size	0.261	0.102**	0.228	-0.194	0.217	-0.649	-0.0109	0.920+	2.676*	-0.482	2.194+
	(0.93)	(3.16)	(1.40)	(-0.28)	(1.57)	(-1.52)	(-0.12)	(2.00)	(2.59)	(-1.08)	(2.02)
Corn Acreage	1.794*	0.189	1.025*	5.015***	1.120	0.929	0.0508	4.402*	12.34***	3.046*	15.39***
	(2.16)	(0.79)	(2.37)	(5.10)	(1.76)	(1.49)	(0.67)	(2.91)	(11.27)	(2.17)	(7.42)
Owner	-0.978+	-0.248	-0.423+	0.0950	0.422	-0.333	0.0872	0.556	-2.243	1.196+	-1.047
	(-1.91)	(-1.42)	(-2.03)	(0.15)	(1.18)	(-0.53)	(1.16)	(0.56)	(-1.28)	(2.11)	(-0.50)
Family Off Farm	45.34	-8.522	55.69	-73.68	20.26	-90.32*	-7.939	-27.11	-180.0	78.05	-102.0
Income (PhP)	(0.28)	(-0.17)	(0.62)	(-1.14)	(0.63)	(-2.56)	(-1.03)	(-0.38)	(-0.63)	(1.06)	(-0.45)
Farmer Off Farm	-35.79	10.18	-50.59	81.60	-18.32	93.27*	7.678	34.59	214.5	-70.53	144.0
Income (PhP)	(-0.22)	(0.20)	(-0.57)	(1.22)	(-0.57)	(2.60)	(0.96)	(0.49)	(0.76)	(-0.96)	(0.64)
Constant	-0.428	0.282	-2.177	2.530	-2.175	6.296*	0.871+	-4.893	2.968	-0.571	2.397
	(-0.08)	(0.19)	(-0.73)	(0.58)	(-1.68)	(2.78)	(2.09)	(-1.03)	(0.25)	(-0.16)	(0.20)
R^2	0.571	0.237	0.543	0.349	0.281	0.308	0.428	0.398	0.259	0.462	0.343
Adj. R^2	0.548	0.196	0.518	0.314	0.243	0.271	0.398	0.366	0.220	0.433	0.308
Observations	510	510	510	510	510	510	510	510	510	510	510

t statistics in parentheses: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Standard errors clustered at the Barangay level.

Appendix B

Proof of Proposition 1

From equation (1b), we know that $\frac{\partial Y}{\partial d} = -\frac{\partial Y}{\partial \tilde{P}}\left(1 - \frac{\partial C}{\partial Y}\right) > 0$ for profit maximization.

Furthermore $\frac{\partial Y}{\partial d}$ is zero when pest pressure is zero. Taking the total differential of equation (1b) with respect to d and P and solving for $\frac{\partial d}{\partial P}$ assuming optimal adjustment of F we obtain:

$$\frac{\partial d}{\partial P} = 1 > 0 \tag{B4}$$

Which implies that pest management labor is increasing in pest pressure. If a farm adopts a pesticidal corn variety (V_p) such that $\frac{\partial P}{\partial V_p} < 0$, where V_p can be thought of as the adoption rate or total planted area of the pesticidal variety, then the chain rule implies that $\frac{\partial d}{\partial V_p} = \frac{\partial d}{\partial P}\frac{\partial P}{\partial V_p} < 0$. This says that labor time dedicated to pest management related tasks decreases as pesticidal crop varieties are adopted proving proposition 1.

Flexible Leisure

If the assumption of fixed leisure is removed from the first order conditions:

$$U_I \mu_F + U_{II} \mu \cdot \mu_F \sigma^2 - U_I w = 0 \tag{B1}$$

$$U_I \mu_d + U_{II} \mu \cdot \mu_d \sigma^2 - U_I w = 0 \tag{20}$$

$$U_I w - U_L = 0 \tag{21}$$

We totally differentiate equations (B1) and (B3) (assuming adoption eliminates pest pressure) and yields the system of equations:

$$U_{II}[\mu_F \partial F + w\partial l + \mu_A \partial A]\mu_F + U_I[\mu_{FF}\partial F + \mu_{FA}\partial A] + U_{II}\sigma^2[(\mu_F^2 + \mu \cdot \mu_{FF})\partial F \tag{B5}$$

$$+(\mu_A\mu_F + \mu \cdot \mu_{FA})\partial A] + U_{II}[\mu_F \partial F + w\partial l + \mu_A \partial A]w - U_{IL}\mu_f[\partial F + \partial l]$$

$$-U_{LI}[\mu_F \partial F + w\partial l + \mu_A \partial A] + U_{LL}[\partial F + \partial l] = 0$$

$$U_{II}[\mu_F \partial F + w\partial l + \mu_A \partial A]w + U_{II}\sigma^2[(\mu_F^2 + \mu \cdot \mu_{FF})\partial F + U_{IL}[\partial F + \partial l]w \tag{B6}$$

$$-U_{LI}[\mu_F \partial F + w\partial l + \mu_A \partial A] + U_{LL}[\partial F + \partial l] = 0$$

Solving the system yields the equation for $\frac{\partial F}{\partial A}$:

$$\frac{\partial F}{\partial A} = \frac{-(U_{II}\delta\sigma^2 + U_I\mu_{FA})(U_{II}w^2 - U_{LI}w)}{\det H} \tag{B7}$$

where the denominator is the determinant of the Hessian of the utility function and $\delta\sigma^2$ is a function of the intrinsic variance. Predictions cannot be made from equation (B7) without making further assumptions about $(U_{II}w^2 - U_{LI}w)$, which measures the relative strength of the income and substitution effects of a marginal income rate increase. In the case here, evidence seem to suggest that the poorer farmers represented in our sample have strong incentives to increase gains rather than leisure[43]. The theoretical framework presented in this dissertation though, implies that increases in on-farm labor time must come from off-farm labor time. Drawing additional on-farm labor time from leisure leads to a similar discussion with the exception that total farm income would increase more quickly in this latter case.

[43] Though the fixed leisure assumption may seem restrictive as it implies that changes in income produce equal changes in the utility for income as well as leisure, qualitative predictions of the model only require that income adjustments affect the desire for work more than it affects the utility for leisure. Studies such as Altman (2001) show that workers may have target income and nonmarket hours. Navarro and Hautea (2014) show that very little of the increases in income from Bt adoption go towards leisure expenditures. Coupled with findings in the CIMMYT report that farmers, especially poorer farmers, see work on the farm as a means to education their children, then the fixed leisure assumption becomes less restrictive.

Proof of Proposition 2:

With the assumption of fixed leisure equation (B1) can be substituted into (B3) yielding:

$$U'\mu_F + U''\mu \cdot \mu_F \sigma^2 - U'w = 0 \qquad \text{(B8)}$$

Totally differentiating equation (B8) with respect to A gives:

$$U''[(\mu_F - w)\partial F + \mu_A \partial A]\mu_F + U'[\mu_{FF}\partial F + \mu_{FA}\partial A] + U''\sigma^2[(\mu_F^2 + \mu \cdot \mu_{FF})\partial F \qquad \text{(B9)}$$

$$+(\mu_A \mu_F + \mu \cdot \mu_{FA})\partial A] - U''[(\mu_F - w)\partial F + \mu_A \partial A]w = 0$$

Rearranging and solving for $\frac{\partial F}{\partial A}$ yields equation 11:

$$\frac{\partial F}{\partial A} = \frac{-\left(\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}\right)}{S.O.C.} \qquad \text{(B10)}$$

where S.O.C. is the second order condition for a maximum and is given by:

$$U''(\mu \cdot \mu_{FF}\sigma^2 + \mu_F^2(1 + \sigma^2) + w^2 - w\mu_F) + U'\mu_{FF} < 0$$

and $\delta\sigma^2 = (\mu \cdot \mu_{FA}\sigma^2 + \mu_A \mu_F \sigma^2 + \mu_A \mu_F - \mu_A w)$ is function of σ^2 the intrinsic variance. Proposition 2 follows.

Proof of Corollary 1:

The second order condition (S.O.C.) for a maximum of equation (B8) is given by:

$$U''(\mu \cdot \mu_{FF}\sigma^2 + \mu_F^2(1 + \sigma^2) + w^2 - w\mu_F) + U'\mu_{FF} < 0$$

implying that the denominator of equation (12) is negative. The term $-\left(\frac{U''}{U'}\right)$ is the Arrow-Pratt coefficient of risk aversion and $\delta\sigma^2 = (\mu \cdot \mu_{FA}\sigma^2 + \mu_A \mu_F \sigma^2 + \mu_A \mu_F - \mu_A w)$ is a function of the intrinsic variance of the production function. The sign of $\delta\sigma^2$ can be determined by noting that the relative sizes of $\mu_A\mu_F$ and $\mu_A w$ are determined by equation (B8) and that all other components of $\delta\sigma^2$ are positive based on model assumptions. Therefore, from equation (B8) we can write $\mu_F = \frac{U'w}{U'+U''\mu\sigma^2} > 0$ since μ_F is constrained to be positive by way of the classical assumptions. Hence, it must be the case that $U' > U''\mu\sigma^2$ since μ_F<0 otherwise.

Therefore:

$$\lim_{|U''\mu\sigma^2|\to U'} \mu_F = \lim_{|U''\mu\sigma^2|\to U'} \frac{U'w}{U' + U''\mu\sigma^2} = +\infty \tag{B11}$$

and

$$\lim_{U''\mu\sigma^2\to 0} \mu_F = \lim_{U''\mu\sigma^2\to 0} \frac{U'w}{U' + U''\mu\sigma^2} = \frac{U'w}{U'} = w \tag{B12}$$

Hence $\mu_F \geq w$ and μ_F diverges from w as risk aversion increases. Given $U'' < 0$, μ_F increases when F decreases, so increasing risk aversion implies a reduction in time applied to tasks F in the pre-harvest period. Most importantly, this completes the proof that $\mu_A\mu_F - \mu_A w > 0$ and therefore $\delta\sigma^2 > 0$.

The above shows that non-pest management farm labor will rise in response to a pure mean increase only if $\mu_{FA} > \left|\left(\frac{U''}{U'}\right)\delta\sigma^2\right|$ since μ_{FA} is always positive when A increases, by design. This proves Proposition 2 above.

Proof of Proposition 3:

For an exogenous change in the intrinsic risk of farm production we totally differentiate equation (B8) w.r.t. σ^2 and F which gives:

$$U''[\mu_F \partial F]\mu_F + U'[\mu_{FF} \partial F] + U''[\sigma^2(\mu_F^2 + \mu \cdot \mu_{FF})\partial F + (\mu \cdot \mu_F)\partial \sigma^2] = 0 \quad \text{(B13)}$$

Rearranging terms and solving for $\frac{\partial F}{\partial \sigma^2}$ yields the equation:

$$\frac{\partial F}{\partial \sigma^2} = -\left(\frac{U''}{U'}\right) \cdot \frac{\mu \cdot \mu_F}{S.O.C.} \quad \text{(B14)}$$

Equation (12) is negative since its denominator is negative, $-\left(\frac{U''}{U'}\right)$ is positive and $\mu \cdot \mu_F$ is positive. This implies that non-pest management farm labor increases when the intrinsic variance of farm yield decreases (proving Proposition 3).

Proof of Proposition 4:

Taking equation (13) and totally differentiating w.r.t. F and A gives:

$$U''[(\mu_F^* - w)\partial F + \mu_A^* \partial A]\mu_F^* + U'[\mu_{FF}^* \partial F + \mu_{FA}^* \partial A] - U''[(\mu_F^* - w)\partial F + \mu_A^* \partial A]w = 0 \quad \text{(B15)}$$

and solving for $\frac{\partial F}{\partial A}$ gives:

$$\frac{\partial F}{\partial A} = \frac{-\left(\frac{U''}{U'}[\mu_F^* \mu_A^* - \mu_A^* w] + \mu_{FA}^*\right)}{S.O.C.} \quad \text{(B16)}$$

From the F.O.C we know that $\mu_F^* \mu_A^* - \mu_A^* w = 0$ and therefore:

$$\frac{\partial F}{\partial A} = \frac{-\mu_{FA}^*}{U'\mu_{FF}^*} \quad \text{(B17)}$$

where the denominator is $U''[(\mu_F^* - w)^2] + U'\mu_{FF}^*$ which simplifies to $U'\mu_{FF}$ since our F.O.C. ensures equality of μ_F^* and w. $\frac{\partial F}{\partial A}$ is positive since $U'\mu_{FF}^* < 0$, and in the second period, $\frac{\partial F}{\partial A}$ only depends on changes in the productivity of time on the farm and not on their degree of risk aversion. Therefore, for a risk-averse farmer, the relative size of a labor response to expected pre-harvest and harvest time changes in mean yield can be expressed as:

$$\frac{\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}}{S.O.C.} < \frac{\mu_{FA}^*}{U'\mu_{FF}^*}$$

since $\frac{U''}{U'}\delta\sigma^2$ is negative and reduces the effect of increases in μ_{FA}.

Appendix C

Table C.1. First Stage Estimates Including Linear Model

	Conditional logit	*Area-level Fixed effects*	*Linear Model*
Seed Price (PHP)	-0.00403*	n/a	n/a
	(0.00227)		
Bt single-trait ×			
Constant	0.320	n/a	-0.476***
	(0.395)		(0.104)
Distance to seed source	0.0288***	0.0139	0.00319
	(0.0105)	(0.00992)	(0.00213)
Rolling terrain	0.815**	0.0812	-0.0109
	(0.337)	(0.323)	(0.0644)
Hilly or mountainous terrain	-0.658*	-1.126***	-0.284***
	(0.342)	(0.362)	(0.0659)
Distance to nearest road	0.288*	0.485**	0.0931***
	(0.171)	(0.218)	(0.0210)
Years farming corn	-0.00313	0.00614	0.000203
	(0.0128)	(0.00775)	(0.00222)
Stacked variety ×			
Constant	2.732***	n/a	0.520***
	(0.646)		(0.122)
Distance to seed source	-0.0510**	-0.0704*	-0.00334
	(0.0216)	(0.0401)	(0.00373)
Rolling terrain	2.132***	1.304*	0.0387
	(0.723)	(0.708)	(0.0793)
Hilly or mountainous terrain	-0.423	-0.895	-0.197*
	(0.435)	(0.635)	(0.0766)
Distance to nearest road	0.128	0.235	0.0473+
	(0.249)	(0.317)	(0.0260)
Years farming corn	0.0195	0.0262*	0.00154
	(0.0205)	(0.0155)	(0.00274)
Observations (choice tasks)	1,320	1,320	1310
Deg. freedom	13	10	69
Log-likelihood	-319.9	-228.6	n/a
Pseudo-R^2	0.324	0.0698	0.503[1]

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.

[1]Refers to Adjusted R^2.

Table C.2. Linear Second Stage Estimates of Unweighted and Area-Weighted Spillovers

	No Spillover	Naïve Linear Model	Linear IV	Naïve Linear Model	Weighted Linear IV
Bt single-trait	-0.0400	-0.270***	1.666	-0.322***	4.977
	(0.109)	(0.0715)	(2.682)	(0.0695)	(16.98)
Stacked Variety	1.048***	0.178	7.515	0.0979	17.98
	(0.164)	(0.138)	(9.526)	(0.135)	(56.26)
Seed Price (PHP)	-0.00167**	0.000125	-0.0150	0.000235	-0.0356
	(0.000604)	(0.000419)	(0.0201)	(0.000400)	(0.114)
GMO Adoption Share		0.932***	-6.925	0.949***	-16.91
		(0.101)	(10.27)	(0.0946)	(56.48)
Constant	0.855***	0.176	5.899	0.171	13.05
	(0.157)	(0.121)	(7.521)	(0.114)	(40.70)
Observations	55	55	55	55	55
Adjusted R^2	0.583	0.843	.	0.859	.
Deg. Freedom	3	4	4	4	4

Standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$