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

ABSTRACT

This study examines the impact of GM crop adoption on farm labor allocation in the Philippines. While GM crops are often thought of as labor saving, little consensus has been reached in the literature regarding this issue. The theoretical framework presented here shows that post adoption labor allocation outcomes will depend on: (1) a direct substitution effect, from the GM crop itself substituting for pest management labor time. (2) A labor crowd-in effect where increases in productivity and decreases in uncertainty at harvest time can increase effort on non-pest management tasks on the farm in the harvest as well as pre-harvest periods. While work has been done on the harvest time impact of GM crops, little has been done to better understand the mechanism through which these crops can affect farm decisions throughout the farm production period (harvest and pre-harvest phases). Predictions from the theoretical framework are empirically investigated using a two-year panel of farmers in the Philippines planting a non-GM hybrid variety and two GM varieties. The GM varieties differentially affect the mean and variance of the yield distribution, isolating their impacts on farming decisions. We find that the positive labor crowd-in effect of GM crop adoption outweighs the labor-saving effect in this context; meaning that pesticidal GM adopting farmers in the Philippines increase effort on the farm relative to non-GM hybrid farmers. We also find that farms of the size represented in the sample are more sensitive to risk effects (i.e., variance effects) than to changes in mean yields. These findings update our understanding of farm input complementarities as the overall impact of pesticidal GM corn is shown here to be context specific.

Keywords: Bt Corn; Genetically-Modified Crops; Labor Savings, Risk Reduction

JEL Classification:

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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) [1] 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 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

[1] 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 (Brookes and Barfoot 2008; Finger et al. 2011; Qaim 2009; Qaim, Pray, and Zilberman 2008; Raybould and Quemada 2010). 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.

decisions of neighboring farms, since increased adoption rates can affect the degree of local pest pressure.

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.

Findings in the literature 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) [2] and their implied harvest time benefits can produce feedbacks on input use incentives even in the pre-harvest phase. For example, Emerick, de Janvry, and Sadoulet (2016) have shown that when producers adopt a "damage abating" [3] 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.[4]

[2] 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.

[3] 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.

[4] 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.

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 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.

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.[5] We will 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:

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

[5] 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.

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[6]. 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. However, to ease the exposition that follows we make one simplifying assumption which is that households have a fixed labor leisure schedule such that leisure is fixed at $\bar{L}$ and simply attempt to maximize expected income by substituting on-farm and off-farm work[7]. Since utility is increasing in farm income, maximizing $U = U(I, \bar{L})$ is equivalent to maximizing:

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

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

[7] 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. Mishra and Goodwin (1997) also show that farm labor under risk is positively correlated with enhancement to the farm yield distribution because labor allocation under risk is likely lower than the neo-classical optimal allocation of labor hours.

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:

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

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

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.[8] 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:

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

and

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

where V is the crop variety that the farm adopts and σ^2 is 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 $\mathrm{E}[Y|A, d, F, X]$ and $\mathrm{E}[(Y-\mu)^2|A, d, F, X, \varepsilon]$ 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:

[8] Figure A1 and results from a White's General Test of heteroskedasticity show that the assumption of heteroskedastic error variance holds in the sample used in the estimation procedure.

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

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

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

Where U and U'' are taken at $\mu + wl + N$, the mean of farm income.[9] Without loss of generality, we assume that leisure is exogenously fixed (i.e., there is a fixed amount of time in a season set aside by the individual for leisure). 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:

$$U'\mu_F + U''\mu \cdot \mu_F\sigma^2 - U'w = 0 \tag{11}$$

$$U'\mu_d + U''\mu \cdot \mu_d\sigma^2 - U'w = 0 \tag{12}$$

which can be combined to form:

$$U'\mu_F + U''\mu \cdot \mu_F\sigma^2 = U'\mu_d + U''\mu \cdot \mu_d\sigma^2 = U'w \tag{13}$$

μ_d[10] 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

[9] 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.

[10] 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.

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. Equation (11) in this context remains the only path for the farmer to respond to changes incurred upon GM crop adoption. Totally differentiating equation (11) with respect to A and F and solving for $\frac{\partial F}{\partial A}$ gives rise to Proposition 2.[11]

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 farmers who are

[11] The proofs of Propositions and Corollaries can be found in Appendix B

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.*[12]

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.[13] 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).[14]

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

[12] **Figure 1** illustrates Corollaries 2, 3 and 4.
[13] 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.
[14] 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.

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.[15] 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: *The relative sizes of $\frac{\partial F}{\partial A}$ and $\frac{\partial F}{\partial \sigma^2}$ depend on the size of the farm.*

Corollary 4 can be derived directly from implications in Corollaries 2 and 3. Figure 1 shows the expected behavior of on-farm work in response to both risk and mean yield changes

[15] 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.

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

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

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.*

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

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.*[16]

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 yield at harvest time and induce a labor change. This secondary response is not directly accounted for in the theory presented here[17]. 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:

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

[16] 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.

[17] 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.

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, 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.

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)[18]. 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.[19]

[18] 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.

[19] 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).

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.

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:

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

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.[20] We argue that including both the 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).[21]

[20] Village specific time trends are used in the estimation procedure.
[21] 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

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:[22]

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

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

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

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

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).

[22] Table A11 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.

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.[23] 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 results were similar to the estimations procedures suggested above and are presented in a separate Appendix document that can be requested from the authors.

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),

[23] 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 can be presented by the authors upon request.

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.

Results and Discussion

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 1. In addition, Table 2 provides descriptive statistics on the labor use across different farm activities (for each variety-survey year combination).[24] In

[24] Descriptive statistics of the remaining independent variables included in the empirical specification in equations 11-13 are presented in Table 3.

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 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 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 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 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 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.

Effects of GM Varieties on Total On-Farm Labor Use

In Table 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 4).[25] 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 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 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.

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

[25] Note that, in Table 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 4. The full specification results are presented in Tables A1 (for total labor use effects across all production activities).

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 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 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 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 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 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 A3). [26]

Combining this with Figure 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

[26] 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 A1 and results from a White's General Test of heteroskedasticity 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 A3.

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 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.

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 Tables 6 to 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 6, effects on family labor in Table 7, and effects on hired labor in Table 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 7. Most of the estimated family labor effects of single-trait Bt and stacked Bt/HT adoption are statistically insignificant (Table 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.

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 A3). 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[27] 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 A2 shows the results of this test[28]. The estimation procedure uses an interaction between the log of wealth and the adoption variables (Bt and Bt/HT dummies) to test how the marginal effect of Bt and Bt/HT adoption changes as wealth changes. 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 made in Corollaries 1 and 2, if farmers have DARA preferences.

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.

[27] 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.

[28] 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.

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.

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.

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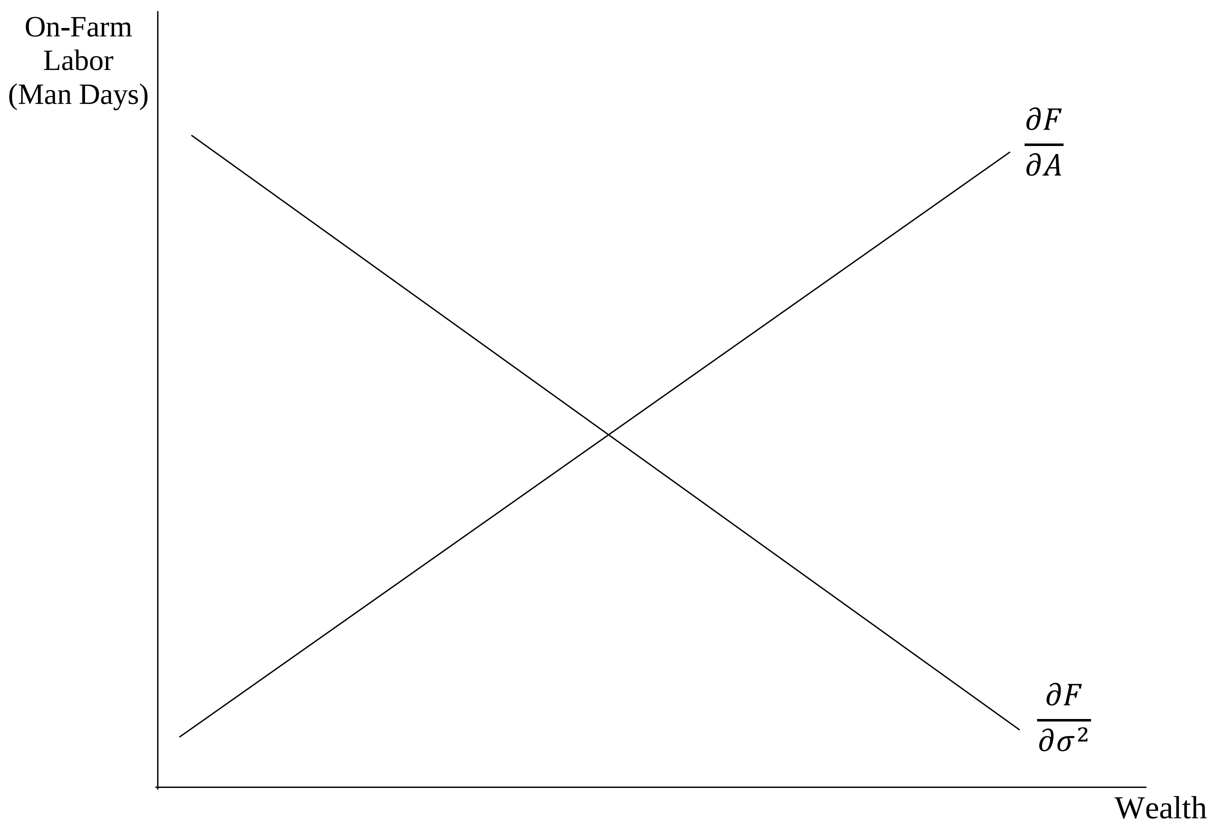

Figure 1. On-farm Labor Response to Changes in Yield Risk (e.g. variance) and Expected Mean Yield Depends on Sensitivity to Risk.

[Note: For farmers with DARA preferences, sensitivity to risk decreases as farm income increases. Figure 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 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 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.					

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. 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 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*	3.42+
	(2.26)	(1.82)
Family	0.02	-5.22
	(0.01)	(-1.11)
Hired	9.93+	19.87+
	(1.67)	(1.89)
All Types (sum labor for all types)[3]	12.34+	18.07
	(1.90)	(1.57)

[1] The figures presented here only reflect the estimated parameters associated with the V_{it}^{Bt} and V_{it}^{Stack} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Appendix Table 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 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}^{Stack} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Appendix Table 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 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}^{Stack} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Appendix Table 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 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}^{Stack} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Appendix Table 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 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}^{Stack} dummy variables. Note that the parameter estimates for the full model specification (i.e., for all variables) are given in Appendix Table 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 observations.

APPENDIX A

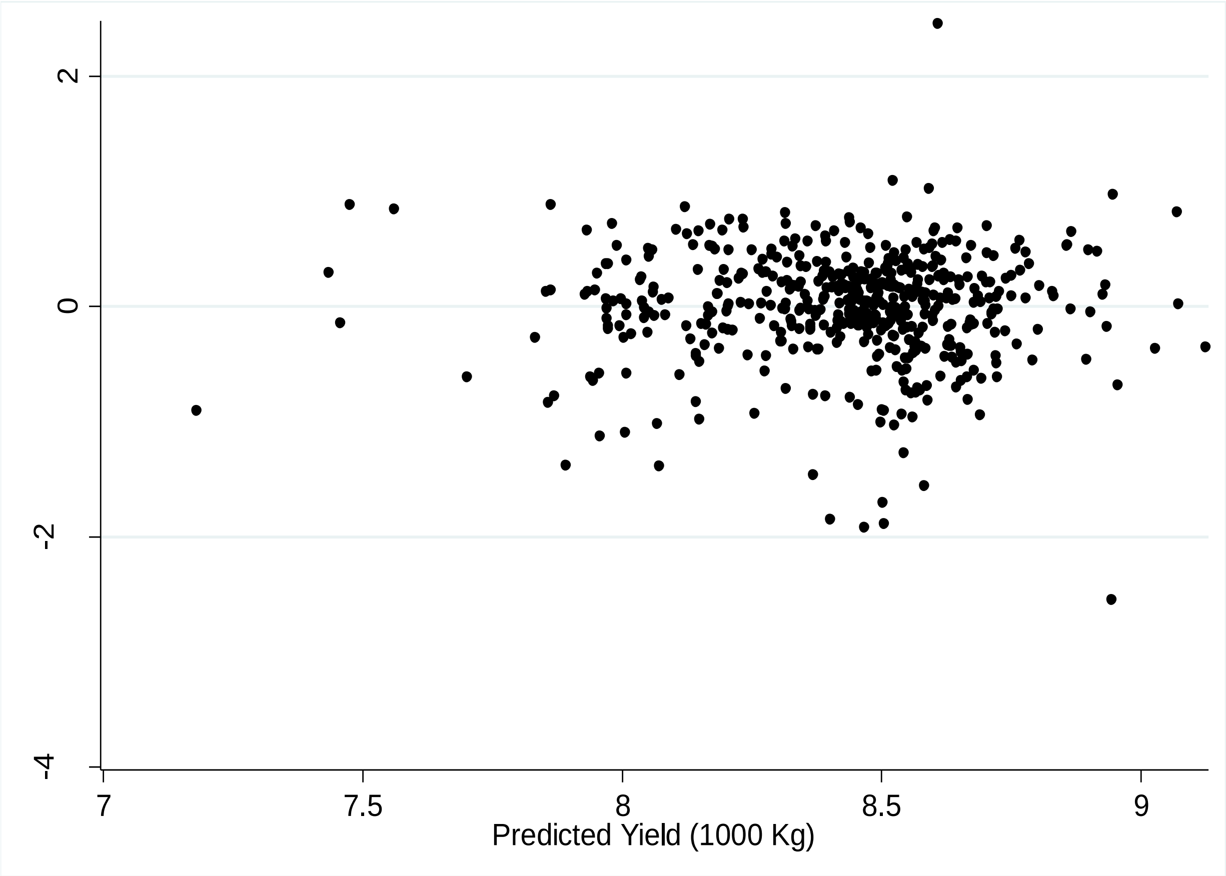

Figure A1. Residual Plots of Yield Regression[1]

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 from a White's General Test of heteroskedasticity show that homoskedasticity can be rejected with greater than 99% confidence.

Table A1. 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:	20.34	-140.8	-160.9	-281.4
Family	(0.26)	(-0.71)	(-0.36)	(-0.58)
Off Farm:	-28.86	113.8	241.4	326.3
Farmer	(-0.36)	(0.56)	(0.53)	(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 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 A2. 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<0.00

Table A3. 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		
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.

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:

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

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.

Proof of Proposition 2:

Totally differentiating equation (8) with respect to A and F gives:

$$U''[(\mu_F - w)\partial F + \mu_A \partial A]\mu_F + U'[\mu_{FF}\partial F + \mu_{FA}\partial A] + U''\sigma^2[(\mu_F^2 + \mu \cdot \mu_{FF})\partial F \\ +(\mu_A\mu_F + \mu \cdot \mu_{FA})\partial A] - U''[(\mu_F - w)\partial F + \mu_A \partial A]w = 0 \tag{B1}$$

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

$$\frac{\partial F}{\partial A} = \frac{-\left(\frac{U''}{U'}\delta\sigma^2 + \mu_{FA}\right)}{S.O.C.} \tag{B2}$$

and proposition 2 follows.

Proof of Corollary 1:

The second order condition (S.O.C.) for a maximum of equation (8) is given by:

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

which is the condition that ensures the existence of a maximum, 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 (8) and that all other components of $\delta\sigma^2$ are positive based on model assumptions. Therefore, from equation (8) 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:

$$\lim_{|U''\mu\sigma^2| \to U'} \mu_F = \lim_{|U''\mu\sigma^2| \to U'} \frac{U'w}{U' + U''\mu\sigma^2} = +\infty \tag{20}$$

and

$$\lim_{U''\mu\sigma^2 \to 0} \mu_F = \lim_{U''\mu\sigma^2 \to 0} \frac{U'w}{U' + U''\mu\sigma^2} = \frac{U'w}{U'} = w \tag{21}$$

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 (8) w.r.t. σ^2 and F which gives:

$$U''[\mu_F \partial F]\mu_F + U'[\mu_{FF}\partial F] + U''[\sigma^2(\mu_F^2 + \mu \cdot \mu_{FF})\partial F + (\mu \cdot \mu_F)\partial \sigma^2] = 0 \quad (22)$$

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

$$\frac{\partial F}{\partial \sigma^2} = -\left(\frac{U''}{U'}\right) \cdot \frac{\mu \cdot \mu_F}{S.O.C.} \quad (23)$$

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:

$$U''[(\mu_F^* - w)\partial F + \mu_A^* \partial A]\mu_F^* + U'[\mu_{FF}^* \partial F + \mu_{FA}^* \partial A] - U''[(\mu_F^* - w)\partial F + \mu_A^* \partial A]w = 0 \quad (24)$$

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

$$\frac{\partial F}{\partial A} = \frac{-\left(\frac{U''}{U'}[\mu_F^* \mu_A^* - \mu_A^* w] + \mu_{FA}^*\right)}{S.O.C.} \quad (25)$$

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

$$\frac{\partial F}{\partial A} = \frac{-\mu_{FA}^*}{U' \mu_{FF}^*} \quad (26)$$

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}.