Do farmers with less education realize higher yield gains from GM maize in developing countries? Evidence from the Philippines

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Abstract

For genetically-modified (GM) maize with genes for insecticidal *Bacillus thuringiensis* (Bt) toxin expression and glyphosate tolerance, there is ample developing world evidence demonstrating general increases in farmer average yields. However, little work carefully examines farmer profiles to explain mechanisms for heterogeneity in yield effects. In this article, we view Bt and stacked traits as *simplifying* input components, removing much complexity in farmer pest control needs. With panel data from the Philippines, we test whether these traits serve as substitutes or complements to human capital. We thus examine an oft-discussed but previously unexplored facet of Bt technology impacts. Results indicate GM traits are substitutes with proxies for human capital and pest control knowledge. For every year *decrease* in formal education and maize farming experience, farmers realize significantly higher yield gains from planting GM maize. This evidence provides additional insights about 'pro-poor' claims of many GM proponents, given small-scale, poor farmers tend to have lower levels of education.

Introduction

The impacts of Genetically modified (GM) crop production in developing countries has attracted considerable attention from researchers and continues to fuel biotechnology policy debates worldwide (Qaim 2009). Particularly important in this debate is how new crop varieties can contribute to global food security and raise small farmer yields and incomes. This debate is not new. During the Green Revolution, the ability of high yielding variety (HYV) crops to benefit the poor was hotly contested, with concerns about skewed technology diffusion (Feder and O'Mara 1981), including access to complimentary physical inputs, credit constraints, and risk aversion (e.g. Smale, Heisey, and Leathers 1995, among many). Complex learning processes to fully capture HYV yield potential and rents may also lead to differential outcomes based on farmer characteristics (Foster and Rosenzweig 1995; Alene and Manyong, 2007). The poorest and least educated farmers thus may have less impetus to adopt innovative crop varieties and, if adopting, could accrue disproportionately lower benefits from the technology.

However, the nature of the seed technology in question is of paramount importance when evaluating potential benefit streams that accrue to farmers with different levels of human capital. Genetic engineering advances have led to ‘bundled’ HYV seeds with both high quality germplasm and inherent insecticidal properties from genes coding for *Bacillus thurengiensis* (Bt) toxin expression. These Bt genes can have a particularly large impact on yields under the right conditions. While yield effects can be more muted in developed country settings with high pest management ability (Shi, Chavas, and Lauer 2013), small developing country farmers in tropical zones with high pest pressure may reap particularly large benefits when insecticide use is low or sporadic (Qaim and Zilberman 2003). Thus, the farmers who potentially stand to gain the most from a technology such as Bt seed are those with low or imprecise input use, and limited knowledge or education. The primary beneficiaries of the new technology therefore may stand in direct contrast to those documented with many previous input innovations in agriculture.

Previous studies have examined yield, price, and market impacts GM maize adoption in South Africa (Gouse et al. 2005, 2006), Argentina (Trigo and Cap 2006), as well as the Philippines (Yorobe and Quicoy 2006; Mutuc, Rejesus, and Yorobe 2011; Mutuc et al. 2012; Sanglestsawai, Rejesus, and Yorobe 2014). However, the link between GM maize in developing country contexts and the role of education and human capital in exploiting potential production benefits has not be tested econometrically. This paper will address this question directly in the context of GM traits increasing maize yields of Filipino farmers.

All studies of GM maize in the Philippines also currently use cross-sectional data, solely relying on instrumental variables to control endogenous selection, and panel data is sorely needed to validate and expand analysis. To address our empirical question, we utilize IFPRI panel data from yellow maize farmers in the provinces of Isabela and South Cotobato in the Philippines, with the panel structure allowing for more precise estimation of GM maize effects.

Background

Bt traits and Filipino maize production

The Philippines is a tropical, lower-middle income country of 99.14M people with a gross national income per capita of $3,470 USD (World Bank 2015). About one third of total employment is in agriculture and arable land per capita is estimated at 0.8 hectares (ibid). After rice, maize is the second largest crop in the Philippines and yellow maize is the most extensive type grown (PSA 2015). In most regions there are at least two maize production seasons per year, in the wet and dry season. In Mindanao, the largest southern island, the major wet season growing period runs from April to September. In Isabela, the largest district of the northern island Luzon, there are two major growing seasons from mid-April to September and mid-November to March. The vast majority of the yellow maize grown in Mindanao and Isabela is sold, primarily to the feed market (Gerpacio et al., 2004). While insecticide use is low, agricultural pest pressure is particularly high in these tropical latitudes and Asian maize borer infestations of 40-60% can lead to over 25% yield loss (Logroño 1998). Farmers estimate much higher losses ranging from 30% to almost complete failure (Mutuc et al. 2012).

Among developing countries, the Philippines has experienced particularly fast growth in GM maize adoption and acreage. By 2014, over 415,000 farmers had adopted GM maize, representing 31% of total maize acres and 63% of yellow maize acres (Aldemita, Villena, and

James 2015; PSA 2015). Figure 1 illustrates this growth of the single trait for Bt, single trait herbicide tolerance (HT), and a 'stacked' combination of Bt/HT traits, from national approval in 2002 until 2014. Introduced in 2006, Bt/HT stacked traits have gradually replaced single trait Bt varieties, while single trait HT maize production has remained relatively stable in absolute terms. It is important to note that in our data set, farmers are only planting single Bt trait and Bt/HT 'stacked' traits, so Bt is always a part of the seed by GM maize adopters.

[Figure 1 about here]

In the Philippines, the vast majority of GM maize includes a Bt trait coding for the production of a synthetic insecticidal toxin. The Bt trait dramatically simplifies insect management, decreasing (but not fully removing) the need for complex and potentially dangerous insecticide application (Qaim and Zilberman, 2003). Poor, inexperienced, and uneducated farmers may be particularly vulnerable to insecticide misuse or poisoning, and adoption of Bt cotton has led to reductions in farmer poisoning in China (Hossian et al., 2004) and South Africa (Bennett et al., 2003). The intrinsic nature of the pesticidal properties of Bt maize may therefore reduce the burden of training and learning in a way which is distinct from past 'modern' inputs and HYV seed technologies. Importantly, the Bt trait in maize has been incorporated exclusively into hybrid varieties for both commercial and agronomic (hybrid vigor) reasons. A farmer facing traditional (i.e. non-'improved') vs. Bt and stacked varieties would therefore face many of the same complexities of managing a hybrid maize production system, with potentially differing input responses.

Human Capital and Agricultural Productivity

Studies both inside and outside the context of agriculture have examined the role of knowledge in the adoption and benefits of new technologies. Extensive reviews have found that, especially in modernizing production environments with new inputs, human capital and education are important in leveraging potential improved input benefits and shifting the production frontier outward (Lockheed, Jameson, and Lau, 1980). However, most previous studies examining the role of knowledge and education in agricultural productivity have centered on total productive efficiency, rather than the role in enhancing (or reducing) the marginal product of a physical input (see: Reimers and Klasen (2013) and references therein). The productive boost has been primarily attributed to the 'worker effect' and the 'allocative effect'. In these mechanisms, the 'worker effect' refers to more efficiency in (given) resource utilization and the 'allocative effect' refers to farmers being more adept at processing information about how to acquire and properly exploit an optimal sub-set of physical resources (Welch 1970; Reimers and Klasen, 2013).

In the case of the complex processes behind production pest control, both are likely important. In short, production pest control is quite difficult, especially at the equatorial latitudes of many developing countries. Effective pest control requires applying the right type of control (i.e. product) at the right time, in the right quantity. The diverse market for pesticides and the importance of optimal application timing, considering pest biology and environmental factors such as precipitation, make this crucial part of the production process truly challenging. Formal education, especially literacy and comfort with arithmetic, may enhance abilities to select proper products, filter recommendations from merchants and/or extension agents, and properly meter dosing. This may contribute to findings by Qaim (2003) that more educated farmers use statistically significantly less pesticide in cotton fields. He claims these producers likely use products more selectively due to greater familiarity with available products and appropriate application schedules. Informal education can similarly improve practical knowledge of pest biology and infestation cycles, anticipating weather patterns, and familiarity with pest risk on one's own land. In a recent study, both formal education and farming experience were shown to be important in objective measurements of farmer production 'pest knowledge' among Kenyan farmers (Abtew et al., 2016). While extension training may contribute as a form of practical semi-formal education, this was (somewhat surprisingly) shown to not be a significant predictor of pest knowledge.

Previous authors have taken these arguments to posit that higher education levels may facilitate a greater increase in agricultural productivity in richer countries, where newer and likely more complex technologies are more present to disrupt traditional equilibria (Shultz 1975). In describing new technologies, the terms 'traditional' and 'simple' tend to be grouped, whereas the concepts of 'new' and 'complicated' are lumped together (e.g. Reimers and Klasen, 2013). In the case of fertilizer-responsive hybrids, irrigation, and agricultural machinery this grouping of newness and complexity may apply. In contrast, biotechnology presents a different genre of potentially 'new' yet 'simpler' technologies where hybrids have already been adopted. The specific pesticidal genes inserted in Bt crops allow for continual expression of toxins, helping to (in part) automatically control some of the most challenging production pests. Significant reductions in pest spraying with Bt planting are widely documented in the developing and developed country literature, as part of simplification of the pest control process (Kirsten and Gouse, 2003; Qaim 2003, Barwale et al., 2004; Gouse et al., 2005, 2006).

The *ceterus paribus* removal rather than addition of complexity from these seed products challenges the notion of more educated or knowledgeable farmers disproportionately increasing agricultural productivity with new technology. If more educated farmers are already outperforming their less educated counterparts in *status quo* pest control, biotechnological trait introductions may help 'level the playing field' by absorbing (i.e. substituting for) the resource allocation advantage which has been previously documented.

Estimation Strategy

Our objective is to measure the impact of human capital and pest knowledge on yield gains from planting GM maize. We use years of formal education and maize farming experience as plausible and tested proxies for pest knowledge (Abtew et al., 2016). Moock (1981) investigates an analogous factor input elasticity problem, interacting education, extension, and experience variables with physical input levels (e.g. fertilizer). Incorporating education and experience in a yield function following Moock (1981), we use a Cobb-Douglas (CD) framework for estimation. In this system, outlined in equation 1, the yield (Y) of an individual *i* in time *t* is a function of *j* inputs X in per-hectare application values. The error term is broken into two components, an individual specific time invariant component c_i and a time varying random component u_{it}.

$$Y_{it} = \prod_{j=1}^{J}(X_{ijt}^{\beta_{jt}})\, e^{c_i+u_{it}} \qquad (1)$$

Non-agricultural input factors are routinely incorporated into yield functions and may or may not impact the elasticities (β_{jt}) of agricultural input factors. An exposition allowing the interaction between input factor elasticity and education is obtained in equation (2). For household *i* in time *t*, the elasticity of yield with respect to each input X_j would be ($\beta_{jt} + \delta_{jt}Educ_{it}$). Experience and extension contact can be similarly incorporated as an interaction term to examine both the role of informal and formal education. Time-varying non-agricultural input factors which may also impact yield are included in a vector $\boldsymbol{Z}$, including extension training, land quality, land size for scale effects (Barret et al., 2010), and a subjective pest pressure coefficient for expected maize borer infestation level.

$$Y_{it} = \prod_{j=1}^{J} (X_{ijt}^{\beta_{jt}+\delta_{jt}Educ_i}) e^{\alpha+\gamma \boldsymbol{Z}_{it}} e^{c_i+u_{it}} \tag{2}$$

To investigate the effect on GM maize yields, an easily estimable regression structure is constructed by including a dummy for GM variety with the appropriate interaction terms and taking logs of yield and other physical inputs in equation (3).

$$\ln(Y_{it}) = \alpha + \varphi GM_{it} + \delta Educ_i GM_{it} + \sum_{j=1}^{J} (\beta_{jt} \ln(X_{ijt})) + \gamma \boldsymbol{Z}_{it} + c_i + u_{it} \tag{3}$$

Identification Strategy

An ideal strategy to identify impacts of GM maize variety yield effects would be through a randomized control trial (RCT) in which participants were randomly assigned an opportunity to plant seeds, particularly if seed type was blinded (Bulte et al., 2014). However, the roll out of GM maize in the Philippines was already underway at the first panel wave in 2007 and a significant number of producers had already adopted. The timing of survey waves and the very rapid uptake of GM varieties make this strategy extremely difficult in our context. Given the data at hand, we employ several strategies to control endogeneity concerns.

Households may be heterogeneous in their ability and incentive to access and adopt GM seed, as well as in their access to information and extension education. Farmers may have unobserved heterogeneity in their information about the benefits of GM seed which could vary greatly over time, given the 250% expansion in production acres accompanied by likely increasing and heterogeneous learning between waves.

Therefore, we attempt to control for potential time-varying endogenous effects via a Control Function (CF) approach (Wooldridge 2010), using the (time varying) distance to seed source and seed price as first-stage exogenous regressors to predict GM seed adoption via a reduced form Probit model. These instruments have been used in previous analyses with the first cross section of this data set to control for potential endogeneity of adoption (e.g. Sanglestsawai et al., 2014). Seed price is a reasonable IV as price clearly influences adoption, yet competitive markets prevent any individual farmer from influencing it. Distance to seed source is also a reasonable IV, as this likely correlates with adoption but not production. Seed suppliers in the Philippines, particularly Monsanto, often offer delivery to the farm which may be particularly attractive for remote producers. This likely results in findings of past studies have shown more distant farmers are more likely to adopt GM seed. Both terms are significant predictors of GM seed adoption, with seed price highly significant ($p<0.001$) and source distance significant at the 90% confidence level ($p=0.083$). In the CF approach, the residuals from the first stage regression are included as a covariate in the second stage estimation. Significance of the residual in the yield regression model provides a test of and an appropriate controls for correlation between GM seed adoption and time-varying shocks.

Data

Data come from two waves of yellow maize producer surveys conducted by IFPRI. All farmers grew fewer than 5 hectares of maize on their main plot. Surveys were conducted for the

2006/2007 growing season and again for the 2010/2011 growing season. The two surveys provide a panel of 256 producers[1] in the South Cotabato province of the southern island Mindanao and in Isabela province on the northern island of Luzon. These zones represent the vast majority of the country's maize growing regions and hot-zones of early GM maize adoption, given extensive targeted private industry marketing. Within these provinces, seventeen major maize-producing villages were selected and yellow maize farmers were randomly sampled from a list, with farmer frequencies determined from a village fixed sampling fraction. We correct for potentially non-random attrition between survey waves using standard inverse probability weights (IPW) (Wooldridge 2010). The procedure involves first using a probit to estimate whether observable factors from the first survey influenced inclusion in the second round, then obtaining these predicted probabilities. The IPW of an individual is thus $IPW = 1/Pr_{iWave2}$. To focus on the highest quality data, only estimates from a farmer's main maize plot (vs. including secondary plots) are reported.

We also include a term for pest pressure. While insect pheromone trap counts are the gold standard in these measurements, the IFPRI data do not include these advanced and very expensive entomological data complements. However, producers were asked "Do you expect lower maize borer infestation this season?". We incorporate this subjective pest pressure insight as a binary measurement to control for environmental factors, taking the value of 1 if "lower" and 0 otherwise. The relative nature of this variable thus provides an imprecise, yet potentially useful component to control for infestation levels.

[1] Sample size varies at times due to occasional missing data

Results

Descriptive Results

Descriptive results from the two waves are displayed in Table 1. *Prima facie* evidence suggests that while yields were increasing overall between waves, average and median yields with GM seed are somewhat higher than hybrid seed. Plot size is generally small, with an average of about 1.3 hectares and a median of one hectare. The sample is predominantly male and 72-73% in each year accessed credit markets in the last season. Notably, while two-thirds of farmers expected lower maize borer infestation in the 2007 wave, this dropped to only 22% in 2011.

[Table 1 about here]

Cross tabulations of mean yields by education and maize farming experience levels (Table 2) provide initial evidence of heterogeneity in yield gains. Across both waves, farmers planting GM varieties have 37.8% higher yields, increasing from an average 3.9 t/ha to 5.4 t/ha. However, this yield advantage peaks at 62.2% among farmers with incomplete primary education (<6 years schooling), declining to 22.6% among those with post-primary studies (>6 years schooling). Similarly, the yield advantage declines from 44.9% for farmers with less than 10 years of maize farming experience to 31.8% for those with greater than 25 years of experience. Interestingly, the absolute yield trend appears to be somewhat increasing with education in hybrid producers but decreasing in GM maize producers. Correlation coefficients between yield and continuous education as well as yield and experience are not significant at the 95% confidence level, however, and we do not further interpret this relationship here. We instead focus on relative percentage yield gains in the following econometric analysis.

[Table 2 about here]

Econometric Results

Fixed Effects Model with Control Function

Fixed Effects (FE) model results are presented to account for time-invariant unobservables. Under FE specifications, the first stage residual is highly significant, adding confidence to endogeneity of GM maize selection and justification for use of the control function. GM maize retains a positive, significant coefficient in each specification, with an average yield effect of 32.8% (column 1). However, this average masks significant heterogeneity. Education and Experience are interacted with GM planting in (2), then included in a full model (3) with additional pest extension training and plot size interactions. Formal education and farming experience are shown to be significantly negatively correlated with GM seed yield effects, adding credence to predictions of substitutability of knowledge inputs and intrinsic pesticidal properties in the seed. Each year of formal education and experience reduces the yield effect by about 5 and 1.5 percentage points, respectively. Extension pest training does not appear to be a significant factor influencing yield effects, though the sign is negative as expected. The size of farmers' maize plot, which have served as the primary point for heterogeneity analysis in GM yields in developing countries (e.g. Gouse et al., 2003, 2004), is also insignificant. The positive coefficient may reflect that pest monitoring becomes increasingly difficult with land area.

To examine potential non-linearities in the effects of education and experience, we also group these terms into logical categorical levels in based on examination of variable kernel densities (available upon request), reporting estimates in column (4). The disparity in yield gains from GM maize is not statistically significant between those with incomplete and complete primary education (stopping at 6 years of education). However, there is a statistically significant 44.9% reduction in GM yield effects between farmers with post-primary (at least some secondary) education and those with incomplete primary. This seemingly runs contrary to findings by Asadulah and Rahman (2009), which suggest basic education is more important for agricultural productivity than higher education. Additionally, we find that compared to farmers with less than 10 years of experience, those with 10-25 and greater than 25 years realize a 40.4% and 53.5% lower yield effect, respectively, from planting GM seed.

Additionally, per hectare labor hours and seed volume planted are significant positive drivers of maize yields. We also demonstrate further evidence for the inverse farm size-productivity theory, with yields decreasing with main plot size, controlling for a (crude yet informative) designation for 'flat' plots.

[Table 3 about here]

Figure 2 presents this yield heterogeneity graphically, with the 95% confidence band for education and experience interaction term estimates (Table 3, column 2). The effect is evaluated at the mean base GM seed coefficient and mean education and experience, constrained to the education and experience range with sufficient data points. At the mean education level of 7.2 years (primary completion at 6 years), the model estimates a mean yield effect of 48.3% for farmers with only 6 years of experience, declining to less than 10% for farmers with over 30 years cultivating maize. At the mean experience level (19.2 years), we estimate a mean yield effect of 45.2% for those with only 4 years of formal education. At 10 years of education, or completion of secondary school, the yield effect has declined to 16.1%.

[Figure 2 about here]

Discussion and Conclusions

We began with the basic hypothesis that the simplifying intrinsic insecticidal properties of GM Bt traits may disproportionately benefit low resource, low educated farmers who are likely to struggle with the complexities of traditional pest management. Using tested proxies from the literature for pest knowledge, our analysis from a panel data set of Filipino maize farmers indicates that GM maize provides a greater yield boost for farmers with both lower formal education and practical maize farming experience. Neither pest training from extension staff nor plot size have a statistically significant effect. The effect of a reduction in formal schooling is over 3 times larger (per schooling year) than the effect of a year less maize farming experience. To the best of our knowledge, this is the first econometric evidence to support a link between GM Bt maize yield gains and human capital in developing countries.

This evidence suggests that GM Bt maize may have particular promise in increasing yields in regions with lower human capital and pest knowledge. Developing countries with struggling rural education sectors, especially those in equatorial regions with severe pest pressure, may particularly benefit. As more countries throughout Asia and Africa consider the legalization and promotion of GM varieties, this evidence could provide an important dimension to consider in policy debates.

This analysis has only compared hybrid non-GM varieties to their GM counterparts. If GM maize is only deployed via hybrid varieties, there may be competing effects of increasing complexity through hybrid varieties and decreasing complexity with GM traits. This may be fertile ground for more research in regions where traditional, hybrid, and GM varieties are simultaneously grown.

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Tables

Table 1: Summary Statistics of Farmer Sample

	2007		2011	
Variable	mean	median	mean	median
Yield (main plot, kg/ha)	3,999	3,750	5,941	5,600
Yield GM seed (main plot, kg/ha)	4,427	4,286	6,035	5,714
Yield Hybrid Seed (main plot, kg/ha)	3,445	3,080	5,390	4,900
Hybrid seed planters (%)	0.44	-	0.15	-
GM seed planters (%)	0.56	-	0.85	-
Insecticide applied (kg/ha)	0.44	-	0.18	-
Insecticide Use (%)	0.37	-	0.09	-
Herbicide applied (kg/ha)	1.03	0.50	2.87	2.00
Seed Vol. (kg/ha)	22.94	18.00	21.06	18.00
Fertilizer applied (50 kg bags/ha)	10.01	8.00	8.58	6.00
Labor (man-days/ha)	28.21	25.00	25.80	17.50
Seed Price (Php/kg)	249.70	255.56	394.63	444.44
Uses Irrigation (1-y,0-n)	0.06	-	0.08	-
Maize plot size (Main plot, ha)	1.31	1.00	1.26	1.00
Owner of Land (1-y, 0-n)	0.03	-	0.04	-
Years Farming Maize (#)	16.36	15.00	19.80	18.00
Household Size (#)	4.48	4.00	4.79	5.00
Borrowed Funds in last season (1-y,0-n)	0.72	1.00	0.73	1.00
Family Off-farm Income (pesos/yr)	3,382	-	6,154	2,000
Farmer Off-farm Income (pesos/yr)	839	-	3,551	-
Farmer Age in Years (#)	42.13	40.00	44.37	43.00
Sex of Farmer (1-male, 0-female)	0.85	1.00	0.85	1.00
Years of Education (#)	7.60	6.00	7.60	6.00
Received Extension Information (1-y,0-n)	0.51	1.00	0.39	-
Received Any Training (1-y,0-n)	0.45	-	0.43	-
Expecting 'Lower' Maize Borer Infestation (1-y,0-n)	0.67	1.00	0.22	-
Distance to Seed Source (km)	6.01	2.00	6.89	5.00

Table 2: Cross Tabulations of Yield (kg/ha) by Maize Type Planted and Education/Experience

Education Level	Hybrid	GM maize	Mean % Diff.	p-value
No primary (<6 years)	3,346 n=30	5,779 n=63	72.7%	<0.001
Primary (=6 years)	3,767 n=45	5,452 n=151	44.7%	<0.001
Post-Primary (>6 years)	4,155 n=58	5,124 n=151	23.3%	0.011
Total	3,848 n=133	5,346 n=365	38.9%	<0.001
Maize Farming Experience	**Hybrid**	**GM maize**	**Mean % Diff.**	**p-value**
<10 Years	4,068 n=30	5,784 n=51	42.2%	<0.001
10-25 Years	3,749 n=81	5,222 n=224	39.3%	<0.001
>25 Years	3,914 n=22	5,326 n=90	36.1%	0.019
Total	3,848 n=133	5,346 n=365	38.9%	<0.001

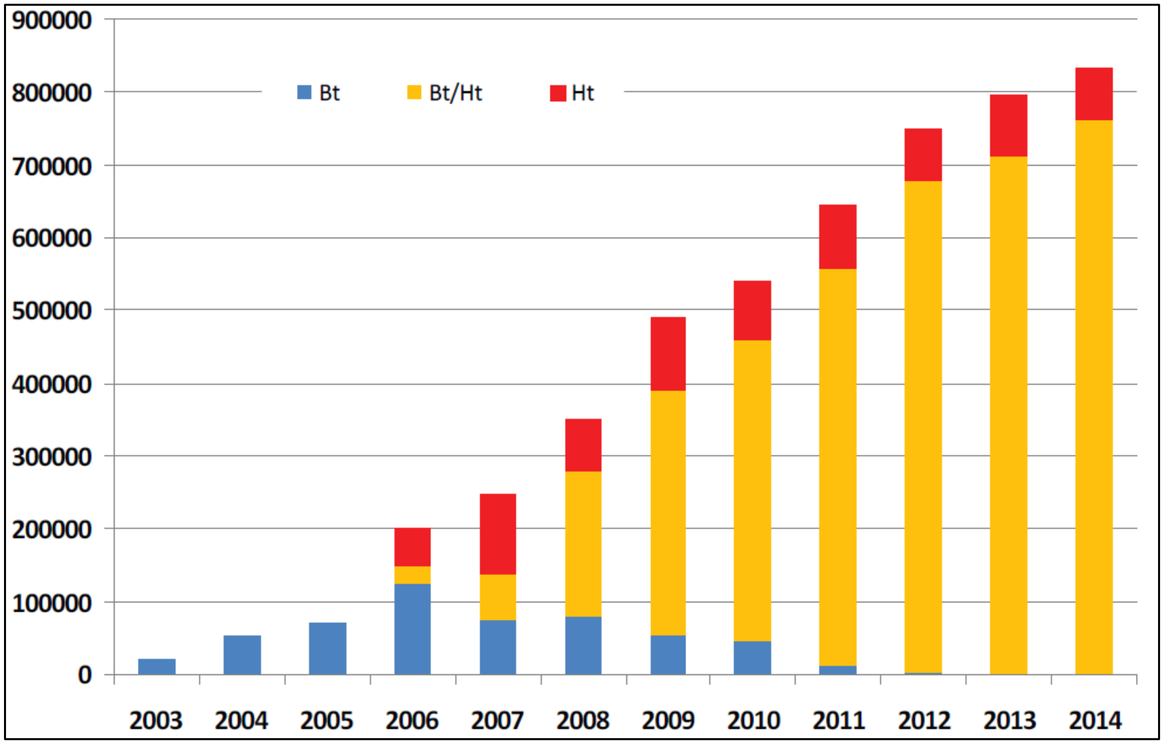
Note: p-values from two-sided mean difference t-tests of Hybrid and GM maize yield rows

Table 3: FE Model of Yield Effects

Dependent Variable: Log yield (kg/ha) / Independent Variables:	FE Model Basic (1)	FE Model with Linear Interactions (2)	FE Model with Full Linear Interactions (3)	FE Model with Categorical Interactions (4)
ResHat_AdoptGMseed	-0.383**	-0.366*	-0.384**	-0.399**
	(0.187)	(0.190)	(0.188)	(0.186)
GM Seed (vs. Hybrid)	0.328**	0.918***	0.909***	0.906***
	(0.149)	(0.254)	(0.250)	(0.247)
GM x Years of Educ.		-0.049**	-0.051**	
(linear)		(0.023)	(0.024)	
GM x Complete Prim. Educ.				-0.171
(vs. Incomplete Prim.)				(0.209)
GM x Post-Primary Educ.				-0.449**
(vs. Incomplete Prim.)				(0.188)
GM x Years of Farming Exper.		-0.014**	-0.015**	
(linear)		(0.006)	(0.006)	
GM x 10-25 Yrs. Farm Exper.				-0.404***
(vs. <10 Years Exper.)				(0.137)
GM x >25 Yrs. Farm Exper.				-0.535***
(vs. <10 Years Exper.)				(0.169)
GM x Pest Training (=1)			-0.078	-0.125
			(0.126)	(0.123)
GM x Plot Size (ha)			0.066	0.105
			(0.074)	(0.078)
Log Seed (kg/ha)	0.241***	0.207**	0.222**	0.220**
	(0.090)	(0.091)	(0.094)	(0.093)
Log Fert. (kg/ha)	-0.011	-0.004	-0.004	0.007
	(0.047)	(0.046)	(0.047)	(0.048)
Log Labor (days/ha)	0.177***	0.189***	0.186***	0.179***
	(0.042)	(0.042)	(0.043)	(0.043)
Log Ins. (kg/ha)	-0.001	0.0004	-0.001	0.001
	(0.013)	(0.013)	(0.013)	(0.013)
Log Herb. (kg/ha)	-0.006	-0.006	-0.007	-0.009
	(0.011)	(0.010)	(0.010)	(0.010)
Maize Borer Expectation	0.093	0.070	0.056	0.065
	(0.082)	(0.077)	(0.078)	(0.075)
Year 2007 (=1)	-0.414***	-0.450***	-0.439***	-0.423***
	(0.089)	(0.086)	(0.088)	(0.086)
Plot Size (ha)	-0.191***	-0.216***	-0.252***	-0.261***
	(0.054)	(0.058)	(0.068)	(0.065)
Flat Plot (=1)	0.129*	0.111	0.117	0.109
	(0.072)	(0.071)	(0.072)	(0.072)
Pest Training (=1)	0.037	0.025	0.090	0.132
	(0.070)	(0.071)	(0.119)	(0.115)
Constant	7.233***	7.404***	7.363***	7.326***
	(0.327)	(0.327)	(0.325)	(0.326)
Obs.	498	498	498	498
R-sq. (within)	0.414	0.436	0.439	0.453

Note: *,**,*** denote significance at the 90,95, and 99% confidence levels. Standard errors (in parentheses) are clustered at the household level.

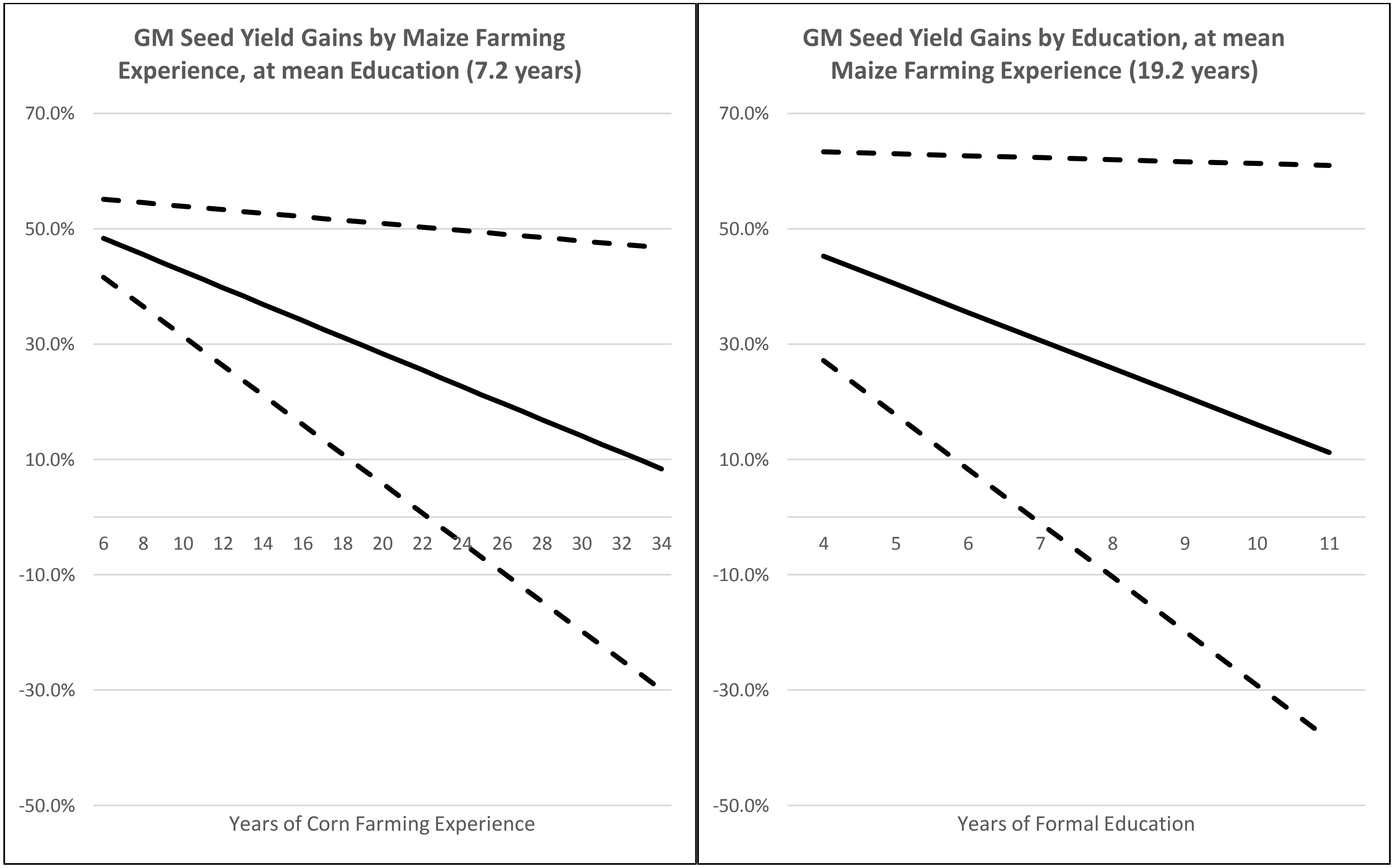
Figure 1: GM maize Area (ha) by Variety in the Philippines, 2003-2014



Source: ISAAA 2014; in Aldemita, Villena, and James 2015

Note: Bt=Bt insecticidal toxin gene; Ht=Roundup-Ready herbicide tolerance

Figure 2: Education and Experience Effects on Yield Gains from GM maize



Note: 95% CI bands represent confidence intervals of Table 2, column 2 GM Seed interaction terms with experience and education, respectively.