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Genetically Modified Crops and Household Labor Savings in US Crop Production

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In spite of widespread adoption, there is mixed evidence as to whether adopting genetically modified (GM) crops increases farm welfare. One possible reason for widespread adoption is the labor savings. Using a treatment effect model we estimate the time savings associated with adopting a GM crop. We find a significant savings in household labor for soybeans, but not for other crops.

Key words: genetically modified crops, agricultural biotechnology, endogeneity, treatment effects, survey weights.

Introduction

Genetically modified organisms (GMOs) have been used in crop production for more than a decade. According to Brookes and Barfoot (2005), the first genetically-modified (GM) crop was the tomato in 1994, followed by GM soybeans. Currently, the most common GMOs in agricultural crops can be classified into two groups: herbicide-resistant (HR) and insect-resistant varieties of corn, cotton, and soybeans. This technology was not developed via conventional crop-breeding methods. Instead, a trait that is foreign to the crop was inserted into its genome. Roundup Ready soybeans are resistant to the herbicide glyphosate, which Monsanto markets under the brand name Roundup. Monsanto developed the Roundup Ready HR trait to serve as a complementary input to Roundup (Just & Hueth, 1993). Glyphosate resistance has also been inserted into corn and cotton. Insect resistance is achieved by inserting a gene from the bacteria *Bacillus thuringiensis* (Bt), which creates a toxin that affects Lepidoptera larvae. Currently the Bt trait has been inserted into corn and cotton to control the European Corn Borer, the Corn Rootworm, the Cotton Bollworm, the Pink Bollworm, the Asian Bollworm, and the Tobacco Budworm.

GMOs are controversial. With the emergence of glyphosate-resistant weeds (Gardner & Nelson, 2008) and the recent accidental release of unapproved GM rice (Endres & Gardner, 2006), the debate over GM crops is not over. The European Union (EU) has a significant aversion to GMOs. According to the US Foreign Agricultural Service (FAS), "biotechnology continues to be more of a political than a scientific issue in Europe and the prospects for improvement remain dim" (US Department of Agriculture [USDA], FAS, n.d., "EU Policy section"). China, another major player in global agricultural trade, also limits GMO production. GMO soybeans, for example, are imported but not grown in China (GMO Compass, 2009). Therefore, it is prudent to continually reassess the economic, environmental, and regulatory issues regarding GM crops. There have been many studies on the welfare impacts of GM crops in US agriculture. In their review of the economics literature, Marra, Pardy, and Alston (2002) broadly concluded that GM crops are profitable for US farmers. However, some evidence suggests that GM crops may not be profitable (Bullock & Nitsi, 2001; Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002). Our objective is to investigate the welfare impacts of GM crops to determine if GM crops are, in fact, profitable for US farmers. If not, then why would farmers adopt a crop that is not profitable? Specifically, we assess whether labor and management savings might be an overlooked benefit of adopting GM crops.

Literature Review

The literature on the economic effects of GMOs is vast, with some *ex-ante* analysis appearing almost a decade before the first GMOs appeared in farmer fields, such as Hueth and Just (1987). A comprehensive review of the literature concerning the welfare impacts of the first generation of GM crops can be found in Marra (2001) and Marra et al. (2002). The authors reached several broad conclusions regarding the literature on the current generation of GM field crops. Bt cotton is likely to be profitable in the cotton belt and reduce pesticide use. Adopting Bt corn should provide a small yield increase, and in some cases adopting causes significant increases in profit. For HR soybeans, they conclude that cost savings should offset any revenue loss due to yield drag. These conclusions seem plausible. Several effects could induce a welfare gain. Carpenter and Gianessi (1999) list four advantages of HR crops. (1) HR technology leads the farmer to substitute relatively less-expensive glyphosate for other herbicides. (2) Farmers realize a change in the shadow price of labor and management.[1]

(3) Due to glyphosate's effectiveness at killing larger weeds, weather-induced spraying delays do not significantly affect weed control. (4) When farmers switch to HR technology, substitution effects lead to a decrease in the price of alternative herbicides. The widespread adoption of GM crops may be evidence of a welfare gain. In 2005, herbicide-resistant crops made up 87% and 60% of US soybean and cotton acreage, respectively, while 35% of the corn acreage and 60% of cotton acres were insect resistant (Fernandez-Cornejo & Caswell, 2005). Bernard, Pesek, and Fan (2004) found that farms in Delaware had yield increases and decreases in weed control costs when they adopted HR soybeans. So, it would seem that adopting this technology results in a welfare gain for farmers. But, as noted above, some studies do not support this conclusion.

Marra (2001) and Marra et al.'s (2002) evidence concerning the profitability of Bt cotton is overwhelming. All of the 47 studies that were compiled indicated that Bt cotton is profitable. Only two HR cotton studies were compiled, and both indicated that the technology was profitable, as did two studies where these two traits were "stacked." However, only two GM corn and soybean papers were included, thus more study is required to develop an assessment of the profitability of these GM crops.

Fernandez-Cornejo et al. (2002) used US Department of Agriculture's Agricultural Resource Management Survey (ARMS) data and concluded that HR soybean adoption did not have a statistically significant effect on farmer profit. The Fernandez-Cornejo et al. study made use of a flexible functional form to estimate a profit function and corrected for endogeneity using an instrumental variables method. Even though the study did not find a profit impact, they did find a small positive yield impact. Bullock and Nitisi's (2001) study, which used a cost-minimizing simulation, found that GM soybean farmers are less profitable than their conventional counterparts. However, they did not take into account the labor and management savings that arise from convenience and timing factors, as these were not observable variables. This leads to a puzzling conclusion; it is uncertain whether HR soybeans are more profitable than conventional soybeans, but almost every farmer uses the technology. Perhaps the research community has been unable to measure an important component of farmers' welfare. Bernard et al. (2004), as mentioned above, did find a positive impact in Delaware. However, they pointed out that Delaware soybean farms are larger than the national average, which may have biased their results.

One overlooked component of farmer welfare might be the time and management savings associated with these crops. In this study, we attempt to measure this impact. Carpenter and Gianessi (1999) cite that the primary reason for adopting HR soybeans is simplicity of weed control and that glyphosate can control a wide range of weeds without harming the HR crop. In other words, HR soybeans require less management. Additionally, Carpenter and Gianessi (1999, pp. 67) point out that "Roundup Ready weed-control programs fit into on-going trends towards postemergence weed control, adoption of conservation tillage practices and narrow row spacing." Glyphosate can also kill larger weeds than other postemergence herbicides, and it has no residual activity, thus it does not limit crop rotation programs. Fulton and Keyowski (1999) discussed the importance of management and cropping practices in their analysis of HR canola in Australia. "The argument that producers benefit if the relative price of growing herbicide tolerant canola falls depends critically on the belief that all farmers are identical in the agronomic factors they face, the management skills they possess, and the technology they have adopted" (Fulton & Keyowski, 1999, pp. 86). In their theoretical model, the authors showed how farmers who use a reduced-tillage cropping practice might find it profitable to adopt HR canola while those who use conventional tillage may not. Fernandez-Cornejo, Hendricks, and Mishra (2005) made an important advancement by explaining high adoption rates for Roundup Ready soybeans in spite of the technology's apparent inability to increase farm profits. Using a household production framework, they found a positive relationship between HR soybean adoption and off-farm income. Their result suggests that adopting HR soybeans can free up resources for alternative uses without decreasing on-farm income. In addition, the result highlights the importance of properly modeling farm production; farms are multi-output producers that generate off-farm income as well as commodity-derived on-farm income.

Using field-level data from the 1997 ARMS survey, McBride and Brooks (2000) compared four soybean-growing regions and found that HR soybeans out-yielded conventional soybeans, except in the Delta Region. They also found that seed cost averaged $10 per acre higher, and pesticide and cultivation costs averaged $8-$12 lower than conventional soybeans. Based on a t-

1. *Farm labor and management has no market price; the price of a non-market good is its shadow price.*

test they found no significant difference between per-acre total production costs. Likewise, they did not find a statistically significant difference in production cost for HR cotton compared to conventional cotton, and they found no significant difference in costs associated with Bt cotton. McBride and Brooks' (2000) results were based on a simple comparison of unconditional means. Unconditional means are an inappropriate tool for comparison because the estimates do not take into account other observable characteristics. An example of this can be found in Marra's (2001) criticism of ARMS results. If you present an average based on Farm A's GM crop and Farm B's non-GM crop, the difference between the estimates cannot be solely attributed to differences between GM and non-GM crops.

Methods

If GM crops save labor and management then the introduction of GM seed should decrease the demand for these inputs. Due to data limitations, it is difficult to measure the quantity or quality of management used on a farm; hence, one can only look at how adopting a GM crop affects on-farm labor usage. Farms are managed by households that allocate labor between on- and off-farm activities. Farms also hire labor, on either a full- or part-time basis, or they may contract out on-farm activities such as pesticide and fertilizer applications or harvesting. We assume that "management" is a component of the labor supplied to the farm from the farm household. Therefore, by focusing on the labor supplied by the farm household, we can more accurately measure the quantity of management used on the farm. A reduction in household labor will reduce management. Because our goal is to measure management as well as labor, we will assume that management is a component of the labor provided by the household, and we will focus our study on household labor. We count all unpaid labor as household labor. This includes the operator, spouse, children, and work performed by friends and relatives.

There is a well-developed set of literature on agricultural household labor allocation between on- and off-farm work. It finds its roots in Becker's (1965) household production model and has been used to model US agriculture. Following Fernandez-Cornejo et al. (2005), one can write the household model in terms of an objective function.

$$Max \quad U = U(q_g, L, l_f), \quad g = (1, 2, \ldots, G), \tag{1}$$

subject to the constraints

$$B = \sum_{g=1}^{G} p_g q_g \leq \sum_{q=1}^{Q} p_q q_q - \sum_{i=1}^{I} w_i x_i + w_o l_o \tag{2}$$

$$T \geq L + l_o + l_f \tag{3}$$

$$w_f l_f = \sum_{q=1}^{Q} p_q q_q - \sum_{i=1}^{I} w_i x_i \tag{4}$$

$$l_o' \geq l_o. \tag{5}$$

Let U denote utility, and let q_g denote the quantity of consumption good g with price p_g. Likewise, q_q and p_q are the quantity and price of the q^{th} agricultural output. Excluding the family labor, denoted by an f subscript, agricultural inputs and prices are x_i and w_i, respectively. Labor supplied to off-farm enterprises and the off-farm wage rate are denoted by l_o and w_o, respectively. Equation 3, which is assumed to hold with equality, states that the amount of time spent in leisure (L) and in labor (l_o and l_f) is bound by the total amount of time available. Farm profit is defined as the return to on-farm labor (Equation 4). The model also assumes that there is minimum off-farm labor requirement (Equation 5), i.e., household members must put in a 40-hour week at a job "in town" to maintain employment or get benefits such as insurance, sick leave, and vacation time. If we assume that household members prefer on-farm work to off-farm work then Equation 5 holds with equality. In addition, we will assume that the time spent working on the farm by the household is a function of the technology (i.e., GM versus non-GM) used on the farm.

$$l_f = l_f(\boldsymbol{g}) \tag{6}$$

The maximization problem outlined in Equations 1 through 6 can be solved in order to obtain the household's demand for on-farm household labor.

$$l_f = l_f\left(\boldsymbol{w}, \boldsymbol{g}\right) \tag{7}$$

In this equation, $\boldsymbol{w}$ is a vector of input prices and $\boldsymbol{g}$ is a GM crop vector. There are two ways to go about estimating the on-farm labor demand. One is to estimate a structural equation model, such as a profit function or a production function. Second, one may estimate a treatment effect model. Heckman (2001) discussed the tradeoffs between estimating a structural equation and a treatment-effect (ATE) model, which we propose to estimate. A structural model, derived from economic theory, is superior to a treatment-effect model. Parameter estimates can be used to answer a wide range of economic questions, and provide well-defined welfare comparisons. However, the theoretical restrictions needed to estimate a valid structural equation are difficult to meet. Reziti and Ozanne (1999) surveyed literature on duality and concluded that an overwhelming number of applied studies reject theoretical regularity conditions. Field-level data is generated in such a way that it will confound the estimation of a traditional production function. A pest infestation, for example, will reduce yield and require more labor. An early-season flood will result in the field being replanted later. These are plausible situations that could lead to an economically implausible estimate—increasing labor decreases yield. Rectifying this problem would require detailed data on the severity and nature of random events.

In contrast to the structural model approach, an ATE model only requires the identification of a small number of parameters. Consequently, it can only be used to answer a small number of research questions. The conditions necessary to identify these parameters are weaker than those required by a structural model. In order to estimate the labor savings associated with adopting a GM crop, we will use an ATE model—as explained by Wooldridge (2002)—to estimate Equation 7, parameterized as

$$\ln(x_l) = \gamma_0 g + \sum_{k=1}^{K} \beta_k x_k + \sum_{k=2}^{K} \gamma_k g x_k . \tag{8}$$

The dependent variable, $\ln(x_l)$, is the natural logarithm of the household labor used in crop production, while g is a dummy variable indicating a GM crop. The remainder of the model is known as the control function, and x_k $(k=1,2,\ldots K)$ are control variables. The objective is to estimate the ATE, γ_0, conditional on the control function. Additionally, the model allows for the estimation of interactions, γ_k , between the GM dummy variable and the control function. Any variable that could explain labor usage is a candidate for the control function (Wooldridge, 2002). The household model discussed above provides theoretical guidance as to the variables used in the control function. The variables used as controls will be discussed below. Identification of the treatment effect requires that the treatment be exogenous. Testing and correcting for endogeneity is a simple matter in a treatment-effect model, assuming that a valid instrumental variable (IV) is available.

If GM crops save labor and management then the introduction of GM seed should decrease the demand for these inputs. Due to data limitations, it is difficult to measure the quantity or quality of management used on a farm; hence, one can only look at how adopting a GM crop affects on-farm labor usage. Assuming that the farm household supplies management to the farm, then a reduction in on-farm household labor may be interpreted as a reduction in management. Our objective is to compare the amount of time spent in a GM field with the amount of time spent in a non-GM field. This difference can be accurately identified after controlling for other factors that may influence labor usage in the field, such as yield, the size of the field, and cropping practice. In addition, the amount of household labor used in the field could vary based on farmer ability and the amount of capital applied to the field. From there, any differences in labor could be attributed to unobserved random events such as weather and pest pressure.

Data and Estimation

Data are from the USDA's Agricultural Resource Management Survey (ARMS). Annual cross-section field-level data for corn, soybeans, and cotton were collected in 2001, 2002, and 2003, respectively. ARMS data are collected using a stratified random sampling and, as such, the USDA provides survey weights that can be used to correct for the survey design.

The dependent variable—unpaid labor—is a full accounting of the time spent working on the farm throughout the growing season by individuals who were not paid for their services. It does not include any form of paid labor, such as full-time, part-time, or seasonal workers; labor provided by custom contractors is also excluded. It is assumed that unpaid workers are members of the household, therefore unpaid labor can be thought of as household labor.

Table 1 summarizes per-acre household labor by crop, tillage practice, and the type of GM seed. Fields planted using the no-till (NT) cropping practice are shown in Table 1 as NT=1. Otherwise, the farmer used some other method. The farmer may have used reduced tillage or conventional tillage, so to avoid confusion we will refer to non-no-till as conventional-till. Using Bt seed is shown as Bt=1, and using HR seed is shown as HR=1. Based on Table 1, it appears that cotton requires more household labor than corn and soybeans. On conventionally tilled cotton fields, HR technology appears to reduce household labor. A no-till, Bt, HR field receives 1.92 hours of household labor, while a no-till

Table 1. Household labor per acre, by crop.

	Soybeans				Corn				Cotton			
	NT=1		NT=0		NT=1		NT=0		NT=1		NT=0	
	HR=1	HR=0	HR=1	HR=0	HR=1	HR=0	HR=1	HR=0	HR=1	HR=0	HR=1	HR=0
Bt=1	NA	NA	NA	NA	+	+	+	2.44	1.44	+	1.92	2.04
Bt=0	0.88	0.82	1.22	1.39	+	1.46	2.34	2.57	1.66	+	2.32	4.35

+ Results suppressed by the USDA to prevent potential disclosure of confidential data.

field with no GM inputs uses 4.35 hours of household labor per acre. On conventional-till corn it appears that Bt fields require more household labor. The no-till practice appears to save household labor in soybeans, but HR does not appear to have a big impact on household labor. In order to comply with USDA National Agricultural Statistical Services' (NASS) confidentiality requirements, we do not present estimates that are based on fewer than 30 observations. Therefore, we cannot use simple means to reach any additional conclusions. Furthermore, the means presented in Table 1 have only been conditioned on tillage practice. Other factors will influence the labor allocation; a well-specified ATE model is required to determine the actual impact of GM crops on household labor allocation.

The objective is to estimate the ATE, γ_0 in Equation 8, conditional on the control function. This can be interpreted as the percentage change in labor usage. Identification of the treatment effect requires that the treatment be exogenous. *A priori*, we expect that the decision to use a GM technology is exogenous because the decision making process that could lead to endogeneity is determined at the farm level, and our data is field level. This belief has support in the literature; Bernard et al. (2004) did not find endogeneity when they studied HR soybean farmers in Delaware. The "treatment variables" are dummy variables indicating the adoption of Bt or HR crops and the adoption of no-till cropping practices. *A priori*, we expected that the coefficients on these variables would be negative. Interaction terms between treatment variables are included when appropriate. For a complete description of variables used in estimation and their means, please see Table 2.

The control variables in Equation 8 are not intended to have any economic meaning, although some of them may be of economic importance. Furthermore, we can still estimate an unbiased treatment effect even if the control variables are endogenous. The control variables are used to condition the treatment effect on observable characteristics (Heckman, 2001). Field size is a great example of the importance of control variables. Obviously, a large field will require more time than a small field; failing to account for field size would result in an omitted variable bias. Farm size is included to control for unobserved capital equipment; larger farms must invest more heavily in capital equipment. Yield can account for unobserved land quality, input usage, weather, and managerial ability, so it is included as a control variable. Herbicide active ingredients, measured in pounds, can control for unobserved pest pressure. In addition to these controls, we include the unpaid wage rate and the wage rate—calculated by the USDA—for

Table 2. Variable means and descriptions.

Variable	Soybeans	Corn	Cotton	Description (coding)
Unpaid labor	36.26	57.13	59.00	Unpaid labor
HR	0.82	0.03	0.75	1 if herbicide tolerant, 0 otherwise
NT	0.41	0.19	0.23	1 if no-till, 0 otherwise
BT		0.04	0.56	1 if Bt, 0 otherwise
Herbicide active ingredient	46.23	77.88	60.31	Herbicide, pounds of active ingredient
Wage	1.37	1.37	4.91	Hourly wage paid to hired labor
Unpaid wage rate	17.95	16.86	19.64	Estimated hourly wage paid to unpaid labor
Production	1705.71	4800.66	25735.60	Total output for the field (bu for corn and soybeans, lbs for cotton)
Farm size	517.42	391.20	1162.42	Farm size
Field size	41.41	36.07	34.67	Field size
Education	0.46	0.40	0.63	Education, 1 if high school graduate, 0 otherwise

paid full-time employees. Although these last two variables—the price of the input and its substitute—are important to include for theoretical reasons, they are potentially endogenous variables and hence have no meaningful interpretation in this context.[2]

The treatment effect, conditional on the observable control variables, can be identified if the treatment is exogenous (Greene, 1997). Any time production data is used in an econometric estimation it is necessary to consider the possibility of endogeneity. In the current context there may be an unobserved component in the error term that is correlated with the decision to adopt a GM crop. Typically, one would test for endogeneity using, for example, the Durbin-Wu-Hausman endogeneity test (Davidson & MacKinnon, 1993). However, hypothesis testing is confounded by the sampling procedure (National Research Council of the National Academies, 2007). Therefore we include both OLS and IV versions of the models. The IV procedure was performed by running two sets of regressions. In the first set, probit models were used to predict the probability of adopting GM crops and no-till cropping practices. In the second, predicted probabilities from the probit models were used instead of the actual dummy variables. As such, the interpretation in the IV model is different. Rather than a percentage change from adopting the technology, the coefficients should be interpreted as the change in the dependent variable when the probability of adopting the technology increases by 1%.

Regression models were estimated using the survey weights supplied with the data. Whenever weighted estimates are used, a robust variance estimate is necessary. According to a recent National Academies report (2007), the jackknife method recommended by the USDA lacks degrees of freedom. Therefore,Huber-White variance estimates are reasonable (National Research Council of the National Academies, 2007).

Results

Estimation results for both OLS and IV can be found in Tables 3 through 5. For completeness, we include test statistics from both the USDA's recommended jackknife procedure and the Huber-White estimates that are part of the standard STATA software output when specifying survey weights. As the motivation behind this research centers on HR soybeans, we will begin by discussing the results from the soybean model (Table 3). Adopting HR soybeans under conventional tillage reduces household-labor by 14.5%, a result that is statistically significant at the 5% level using the Huber-White variance estimator and at 10% using the jackknife estimate. The HR coefficient is negative and statistically significant in the IV model as well, however, the interpretation of the coeffi-

Table 3. Soybean labor model.

Variable	OLS, robust variance estimates	OLS, jacknife variance estimates	IV, robust variance estimates	IV, jacknife variance estimates
HR	-0.145** (-2.323)	-0.145* (-2.077)	-0.222* (-1.891)	-0.222** (-2.717)
NT	-0.375*** (-3.764)	-0.375** (-2.804)	-0.370* (-1.890)	-0.37* (-2.006)
HR*NT	0.0694 (0.650)	0.069 (0.49)	0.0703 (0.324)	0.07 (0.407)
H active ingredient	-0.0124 (-0.442)	-0.012 (-0.491)	-0.00553 (-0.162)	-0.006 (-0.182)
Wage rate	-0.263*** (-7.377)	-0.263*** (-10.356)	-0.261*** (-7.333)	-0.261*** (-10.56)
Unpaid wage rate	0.332 (1.199)	0.332 (1.424)	0.336 (1.176)	0.336 (1.467)
Production	0.0686 (1.318)	0.069 (1.405)	0.0719 (1.261)	0.072 (1.287)
Farm size	-0.114*** (-5.707)	-0.114*** (-6.117)	-0.114*** (-4.949)	-0.114*** (-4.279)
Field size	0.694*** (9.725)	0.694*** (10.752)	0.676*** (8.946)	0.676*** (10.996)
(Production)^2	0.000264 (0.0267)	0 (0.012)	0.000202 (0.0198)	0 (0.008)
(Farm size)^2	-0.0297*** (-2.681)	-0.03** (-2.357)	-0.0316*** (-2.720)	-0.032** (-2.331)
(Field size)^2	0.0348 (1.338)	0.035 (1.2)	0.0339 (1.334)	0.034 (1.035)
Education	-0.0811 (-1.518)	-0.081 (-1.351)	-0.0726 (-1.347)	-0.073 (-1.349)
Constant	1.481*** (7.668)	1.481*** (6.585)	1.557*** (6.960)	1.557*** (6.119)
Observations	1880	1880	1833	1833
R-squared	0.634	0.634	0.615	0.615
F	151.0***	151.0***	143.9***	143.9***

**** p<0.01, ** p<0.05, * p<0.1; t statistics in parentheses*

2. *An early draft of this section included interactions between the GM crop dummy variables and the control function variables, as well as state dummy variables. These variables were either insignificant or collinear and thus dropped from the model.*

Table 4. Corn labor model.

Variable	OLS, robust variance estimates	OLS, jackknife variance estimates	IV, robust variance estimates	IV, jackknife variance estimates
HR	-0.0100 (-0.0728)	-0.01 (-0.083)	-0.0298 (-0.120)	-0.03 (-0.097)
NT	-0.173*** (-2.597)	-0.173** (-2.207)	-0.272*** (-2.604)	-0.272* (-1.854)
HR*NT	0.0691 (0.297)	0.069 (0.229)	-0.0643 (-0.316)	-0.064 (-0.212)
BT	0.145 (1.314)	0.145 (0.961)	0.0418 (0.105)	0.042 (0.138)
NT*HR	-0.0470 (-0.371)	-0.047 (-0.252)	0.0129 (0.0797)	0.013 (0.054)
BT*HR	0.425** (1.998)	0.425 (1.345)	0.395 (1.630)	0.395 (1.132)
Active ingredient	-0.0223 (-1.416)	-0.022** (-2.247)	-0.0232 (-1.299)	-0.023** (-2.423)
Wage rate	-0.210*** (-5.236)	-0.21*** (-3.762)	-0.234*** (-7.097)	-0.234*** (-5.402)
Unpaid wage rate	0.108 (0.314)	0.108 (0.264)	-0.0637 (-0.221)	-0.064 (-0.192)
Production	0.125*** (2.948)	0.125*** (3.527)	0.0901*** (2.603)	0.09*** (7.751)
Farm size	-0.212*** (-5.007)	-0.212*** (-4.988)	-0.169*** (-7.409)	-0.169*** (-7.395)
Field size	0.617*** (10.35)	0.617*** (13.677)	0.637*** (10.63)	0.637*** (26.56)
(Production)^2	0.0214*** (3.913)	0.021*** (6.516)	0.0184*** (3.399)	0.018*** (8.354)
(Farm size)^2	-0.00930 (-0.752)	-0.009 (-0.668)	-0.00295 (-0.264)	-0.003 (-0.237)
(Field size)^2	-0.0264 (-1.420)	-0.026 (-1.281)	-0.0351* (-1.845)	-0.035* (-1.766)
Education	-0.0797 (-1.128)	-0.08 (-1.08)	-0.0780 (-1.160)	-0.078 (-1.115)
Constant	1.746* (1.767)	1.746 (1.468)	2.265*** (2.729)	2.265** (2.372)
Observations	1861	1861	1830	1830
R-squared	0.588	0.588	0.606	0.606
F	87.82***	87.82***	80.53***	80.53***

**** p<0.01, ** p<0.05, * p<0.1; t statistics in parentheses*

Table 5. Cotton labor model.

Variable	OLS, robust variance estimates	OLS, jackknife variance estimates	IV, robust variance estimates	IV, jackknife variance estimates
HR	-0.694** (-2.022)	-0.694 (-1.375)	-0.862 (-1.589)	-0.862 (-1.355)
NT	0.231 (0.917)	0.231 (0.821)	-1.799 (-1.247)	-1.799 (-1.243)
HR*NT	-0.426 (-1.411)	-0.426 (-1.000)	1.778 (1.163)	1.778 (1.166)
BT	-0.825** (-2.328)	-0.825 (-1.737)	-0.93 (-1.184)	-0.93 (-1.009)
NT*HR	0.611* (1.735)	0.611 (1.265)	0.875 (1.051)	0.875 (0.998)
BT*HR	0.0481 (0.217)	0.048 (0.164)	-0.041 (-0.240)	-0.041 (-0.173)
Active ingredient	-0.0346 (-0.543)	-0.035 (-0.374)	-0.062 (-0.776)	-0.062 (-0.673)
Wage rate	-0.319*** (-5.251)	-0.319*** (-3.936)	-0.313*** (-5.847)	-0.313*** (-4.02)
Unpaid wage rate	-0.0998 (-0.110)	-0.1 (-0.082)	-0.058 (-0.0123)	-0.058 (-0.05)
Production	0.139 (1.049)	0.139 (0.665)	0.099 (0.649)	0.099 (0.439)
Farm size	-0.175*** (-3.121)	-0.175** (-2.595)	-0.174*** (-3.115)	-0.174*** (-2.987)
Field size	0.577*** (3.352)	0.577** (2.409)	0.63** (2.580)	0.63** (2.295)
(Production)^2	0.0120 (0.938)	0.012 (0.551)	0.008 (0.549)	0.008 (0.334)
(Farm size)^2	-0.102*** (-3.177)	-0.102 (-1.682)	-0.092 (-2.866)	-0.092 (-1.552)
(Field size)^2	-0.0237 (-0.668)	-0.024 (-0.554)	-0.033 (-0.886)	-0.033 (-0.815)
Education	0.142 (0.702)	0.142 (0.464)	0.156 (0.633)	0.156 (0.521)
Constant	2.955 (1.178)	2.955 (0.938)	3.193 (1.185)	3.193 (1.041)
Observations	1269	1269	1269	1269
R-squared	0.426	0.426	0.405	0.405
F	30.17***	30.17***	29.72***	29.72***

**** p<0.01, ** p<0.05, * p<0.1; t statistics in parentheses* cient changes. If the probability of adopting HR soybeans increases by 1%, then household labor decreases by 0.22%. This result explains how the literature on HR soybeans has not found a conclusive profit effect in spite of widespread adoption. The result is also consistent with Fernandez-Cornejo et al.'s (2005) findings. It appears that farmers are substituting HR soybeans for household labor, freeing up labor and management for off-farm employment, leisure, or the expansion of the farm. This result lends credence to Fernandez-Cornejo et al.'s (2007) conclusion that small farms adopt labor-saving technology so that they may dedicate more time to off-farm work. Although not the primary focus of this study, the no-till coefficient is also of interest; adopting a no-till cropping practice, conditional on using conventional soybean seeds, results in a 37.5% reduction in household labor, a result that is statistically significant. According to the IV version of the model, if the probability of adopting no-till increases 1% then the household labor use decreases by 0.37%, a result that is statistically significant at the 10% level. It is tempting to interpret the HR*NT coefficient as the labor savings from simultaneous adoption. However, this is not the case. One would need to first use an F-test to verify that the HR, NT, and HR*NT coefficients are jointly significant and then sum the coefficients. However, given the survey design, the results of such a test are unclear (National Research Council of the National Academies, 2007).

The results from the corn model provide an interesting contrast to the soybean results. Biotechnology does not appear to have a statistically significant impact on household labor. Only the coefficient for stacked technology (BT*HR) is statically significant, but only in one of the four models. The no-till coefficient in all four models is negative and statistically significant. Concerning the Bt technology, this result can easily be explained. In the absence of Bt technology, many corn farmers simply do not attempt to control for corn borers (Fernandez-Cornejo & McBride, 2002). Thus, one should not expect to see a difference in the labor usage between Bt and non-Bt corn crops. As discussed above the literature has demonstrated a clear welfare gain from the adoption of Bt corn, thus it is not surprising to see adoption of this technology in spite of the absence of a labor savings.

Similar to the corn model, the evidence for cotton is weak. When using an IV method, none of the biotechnology coefficients is statistically significant. However, in the OLS model, when the Huber-White robust variance estimators are used, the HR and BT coefficients are statistically significant, implying that Bt cotton may save household labor. This result is not surprising, as cotton growers have had a long-standing battle against insect pests. Conventional cotton crops require frequent spraying; Bt cotton requires less spraying. This difference amounts to an 82.5% decrease in household labor. In addition, HR cotton also reduces household labor by 69%. This result should be viewed with caution—when accounting for potential endogeneity the coefficient is not significant and the method used to calculate standard errors has an impact on statistical significance. When using the USDA's replicate weights to calculate jackknifed standard errors, the coefficient is not significant, but when using the Huber-White robust estimator, the coefficient is significant at the 5% level. This could be due to the jacknife's low degrees of freedom. As discussed in the literature review, Bt cotton increases profit due to reduced pest-control cost and increased yield. If the value of household labor was not counted in previous studies then this result implies that the true welfare is higher.

Table 6. Estimated household labor savings.$^{+,++}$

	Soybeans	Corn	Cotton
Total planted acres	517.42	391.20	1162.42
Average household labor per acre	1.39	2.57	4.35
Average household labor hours per field	719.21	1005.38	5056.53
HR household labor savings	14.50%$^{+++}$	1.00%	69.40%
Total HR household labor savings	104.29	10.05	3509.23
Bt household labor savings	NA	14.50%	82.50%
Total Bt household labor savings	NA	145.78	4171.63
NT household labor savings	37.50%$^{+++}$	17.30%$^{+++}$	23.10%
Total NT household labor savings	269.71	173.93	1168.06

$^{+}$ *OLS model*

$^{++}$ *Household labor includes spouse, operator, children, and all other unpaid labor.*

$^{+++}$ *Statistically significant at conventional levels, and robust with respect to statistical method.*

Summary

To demonstrate the interpretation of these results, consider Table 6, which shows the average number of planted acres (i.e., the farm size), the average household labor per acre, and the labor savings associated with each technology. Assume that a farmer has an average-sized soybean farm (517.4 acres), and employs conventional tillage without using HR seed. The average amount of household labor per acre is 1.39 hours. OLS model results indicate that complete adoption of HR soybeans will reduce the quantity of household labor applied by 14.5%, for a total of 94.5 hours, or about 10, 9.5-hour days throughout the growing season. A result that is both statistically significant and economically significant. A part-time farmer can use this time to work at his/her off-farm job. It is difficult to place a value on this time, as it could be used for leisure or to generate off-farm income. The same farm could save 270 hours of household labor by adopting no-till practices. The average corn farmer can reduce household labor by 173 hours by adopting no-till practices, but does not seem to realize a labor savings from adopting biotechnology. The average cotton farmer could potentially reduce household labor hours by an economically significant amount—3,509 hours from adopting HR seed and 4,171 hours by adopting Bt seed. However, the cotton results should be viewed with a great deal of skepticism, as the statistical significance of the coefficients depends highly upon the estimation method and the method used to compute standard errors.

This study is the first known estimate of the labor savings associated with GM crops. We assume that all unpaid labor is household labor, and use field-level data to estimate an ATE model. We find strong evidence that HR technology can generate a significant savings in household labor for soybeans, weak evidence of household labor savings in cotton and no evidence of household labor savings in corn. Adopting HR soybeans reduces labor usage, on average, by 14.5%. This result fills a significant gap in the literature, and explains why soybean growers have readily adopted HR technology in spite of an apparent lack of a welfare gain. Additionally, this result points us in a different direction for future research on the farm-level impacts of biotechnology. It is important to properly value unpaid labor, and one must consider how these technologies affect non-farming activities such as leisure and off-farm employment.

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