Genetically Modified Organisms and Agricultural Productivity[1]

Robert G Chambers[2] and Yu Sheng[3]

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[2]University of Maryland
[3]Peking University

Introduction

Increasing global living standard requires increasing agricultural productivity. A large body of research suggests that biotechnological innovations in the form of genetically modified organisms (GMO) promise to revolutionize agricultural productivity (for example, Wheeler and Von Braun 2013; Bailey-Serres et al. 2019; Eshed and Lippman 2019; Zaidi et al. 2019). But empirical measures of the effects of GMO techniques on agriculture's productivity as a sector are lacking. Available evidence on GMO's agricultural impact comes from laboratory experiments, farm-level studies, and regional-level studies. While valuable, these analyses cannot capture the macroeconomic phenomena that affect agriculture's role in promoting sustainable development.

Using a newly available data set that covers 15 OECD countries for the 1973-2011 period, we study the impact of adopting GMO techniques on aggregate agricultural productivity. Because of data availability, our study focuses on the agricultural sectors of richer countries. Nevertheless, it may have important implications for future agricultural development in poorer nations. Agricultural productivity differences between richer and poorer nations are remarkably large (Caselli 2005; Restuccia et al. 2008; Lagakos and Waugh 2013; Adamopoulos and Restuccia 2014). Because agricultural employment dominates non-agricultural employment in developing economies, closing the agricultural productivity gap between poorer and richer nations may be critical to lifting living standards world wide. And understanding agricultural-productivity drivers in richer countries is crucial to identifying opportunities for improving poorer-countries' agricultural productivity. This paper studies whether adopting GMO techniques enhances sectoral agricultural productivity. Surprisingly, given existing micro-level evidence, the answer appears to be no.

The analysis proceeds as follows: We first introduce a productivity accounting framework that distinguishes between GMO and non-GMO aggregate production processes. We then discuss our data, present the basic empirical results, and detail robustness checks for our findings. The paper closes with a discussion of the implications of our analysis.

The Model

We assume that aggregate agricultural value added, Y, is a function of aggregate agricultural capital, K, and aggregate agricultural labor, L:

$$Y = AK^b L^{1-b}. \tag{1}$$

Dividing both sides of (1) by L and taking natural logarithms gives:

$$\ln y = a + b \ln k,$$

where $a = \ln A$ and lower-case letters are variables expressed in per unit of labor terms, $y = \frac{Y}{L}$ and $k = \frac{K}{L}$. Value added per unit of labor (*labor productivity*, LP), y, has two drivers: *agricultural productivity* (AP) measured by A and *capital intensity*, k. [1]

We assume that GMO techniques and non-GMO techniques represent different production processes. To distinguish potential outcomes from observed outcomes, we denote by

$$\ln y\,(0) = a\,(0) + b\,(0) \ln k$$

the non-GMO process and by

$$\ln y\,(1) = a\,(1) + b\,(1) \ln k$$

[1] Our data on capital and labor were constructed using hedonic adjustments over time and other dimensions to accommodate non-neutral technical differences over time. Hence, our empirical investigation focuses on factor-neutral AP. The parameter,

$$A = \frac{Y}{K^b L^{1-b}},$$

measures value added per unit of the aggregate input $K^b L^{1-b}$. In the macroeconomic growth and development literatures, which focus on returns to aggregate captial and labor, it is often called either *total factor productivity* or *efficiency*. The former is more common in intertemporal analyses, and the latter in cross-country analyses. In intertemporal analyses, such changes in total factor productivity are usually identified with technical change. In cross-country analyses, differences are interpreted as country-specific productivity differences. This definition of total factor productivity, however, differs from that employed, for example, in official US statistics reported by the Economic Research Service, United States Department of Agriculture (see https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-u-s/). Their definition of TFP is total agricultural output (and not value added) divided by total agricultural input use. To prevent confusion, we use the AP terminology in our study.

the GMO process. Let G be an indicator variable with value 1 for a GMO process and 0 for a non-GMO process. Letting $\ln y$ denote the observed natural log of LP gives the following relation between observed and potential outcomes:

$$\begin{aligned} \ln y &= G \ln y(1) + (1-G)\ln y(0) \\ &= a(0) + b(0)\ln k + \alpha G + \beta G \ln k. \end{aligned}$$

Here $\alpha \equiv a(1) - a(0)$ measures the AP difference between a GMO and non-GMO process, and $\beta \equiv b(1) - b(0)$ measures the differential between the output elasticity of capital for a GMO and non-GMO process. These parameters are the focus of our analysis.

To link our conceptual model to an observational setting, we use the empirical specification:

$$\ln y_{it} = c_0 + u_i + v_t + b_0 lnk_{it} + \alpha G_{it} + \beta G_{it} \ln k_{it} + \epsilon_{it}. \tag{2}$$

Here subscripts it denote the ith country at time t, u_i is a country-specific AP effect that controls for cross-country productivity differences, v_t is a time-specific AP effect that controls for time-varying productivity differences, and ϵ_{it} is a white-noise, productivity error component.

To estimate this structure, we must accommodate three econometric challenges. GMO adoption is not randomly assigned across countries, which raises the potential for sample-selection issues. Second, a country's GMO adoption decision as well as its capital investment likely depends on macroeconomic factors, public attitudes, and other omitted variables external to our model. Finally, countries adopting GMO techniques do so with different intensities at different time periods. An annex details our methods for dealing with each of these problems.[2]

The Data

The data are for 15 OECD countries for the period of 1973-2011.[3] They extend data sets detailed in Ball et al. (2001, 2010) and Sheng et al. (2015). The agricultural production

[2]Please refer to Annex A for more details.

[3]The countries are: Belgium, Luxembourg, Germany, France, Spain, Italy, the Netherlands, the United Kingdom, Ireland, Sweden, Denmark, Finland, the United States, Australia, and Canada.

account data consist of a country-by-year panel of price and quantity indexes for three outputs (crops, livestock, and other non-separable activities) and four inputs (capital, land, labor, and intermediate inputs).

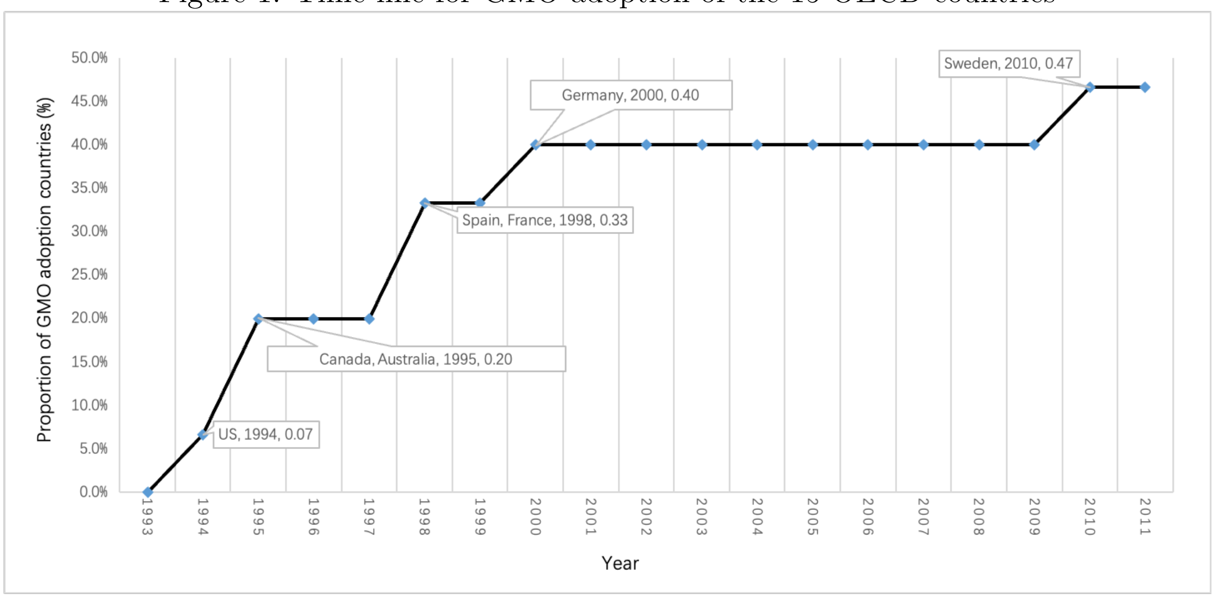
Our aggregate performance measure is real output value added in the farm sector (agriculture, excluding forestry and fisheries). It is calculated using gross agricultural output value (the sum of output of agricultural goods and the output of goods and services from non-separable secondary activities) minus the total value of intermediate inputs, deflated by the relative price of aggregate agricultural output. We evaluate agricultural output from the producer perspective. That is, subsidies are added to and indirect taxes are subtracted from market values. In those countries where a forfeit system prevails, the difference between payments and refunds of the tax on value added (or VAT) is included in the value of output.

Our model considers two aggregate inputs, capital and labor. Other inputs are aggregated into a single aggregate, intermediate inputs, whose value is then subtracted from aggregate output to create value added. The labor input is measured by aggregating hours worked by hired and self-employed (and unpaid family workers) workers using the corresponding compensation as weights. The compensation of hired farm workers is defined as the average hourly wage plus the value of perquisites and employer contributions to social insurance. The compensation of self-employed workers is derived by using the accounting identity where the value of total output value is equal to total factor outlay. Quality adjustments have been made to account for the difference in age, education and gender of rural labor force across countries over time.

Capital consists of land and depreciable capital assets including non-dwelling buildings and structures, plant and machinery, and transportation vehicles. Capital input (or capital services) is derived from capital stocks based on the constant efficiency model with a set of assumptions to model variations in service lives (Ball et al. 2008, 2001; Sheng et al. 2020). Capital stock of depreciable assets is constructed as a weighted sum of past investments for each type of asset. The weights correspond to the relative efficiencies of capital goods of different ages, so that the weighted components of capital stock have the same efficiency. Capital stock of land is constructed as the ratio of the value of land of different types in agriculture to the corresponding price index. The price index of land is estimated using hedonic methods that allow for spatial differences in land characteristics or quality. This treatment provides a means of incorporating important but difficult to measure factors such as environmental and natural resource endowments into the capital measure.

Finally, we measure GMO adoption by constructing a time-variant dummy for each country using the data on GMO approval events from International Services for the Acquisition of Agri-biotech Application (ISAAA, 2019). The dummy variable takes one in a country for each year after the first GMO event has been commercially adopted, and otherwise zero. Through the period of 1973-2011, 7 out of the 15 OECD countries have approved GMO commercial use. They are the United States (1994), Canada (1995), Australia (1995), Spain (1998), France (1998), Germany (2000), and Sweden (2010). Figure 1 illustrates the GMO adoption time line.

Figure 1: Time line for GMO adoption of the 15 OECD countries



Note: The data are from GMO approval database (ISAAA, 2019), available online at http://www.agropages.com/AgroData/.

Empirical Analysis

Table 1 presents summary sample statistics on labor productivity, y, and capital intensity, k, segregated according to eventual adoption strategy. Figure 2 presents a box-plot of y also segregated over eventual adoption strategy. The vertical line between 1993 and 1994 separates the "pre-GMO" period from the period after the first commercial adoption of GMO techniques. LP for both adopters and non-adopters exhibits an upward trend over the entire sample period, although its growth appears slower for both after 1993. On average, LP for GMO adopters is approximately 15% higher than that for non-adopters. But the dispersion of LP for non-adopters is greater than that for GMO adopters. For example, the countries with the highest LPs are non-adopters and with few exceptions so are the countries with the lowest LPs.

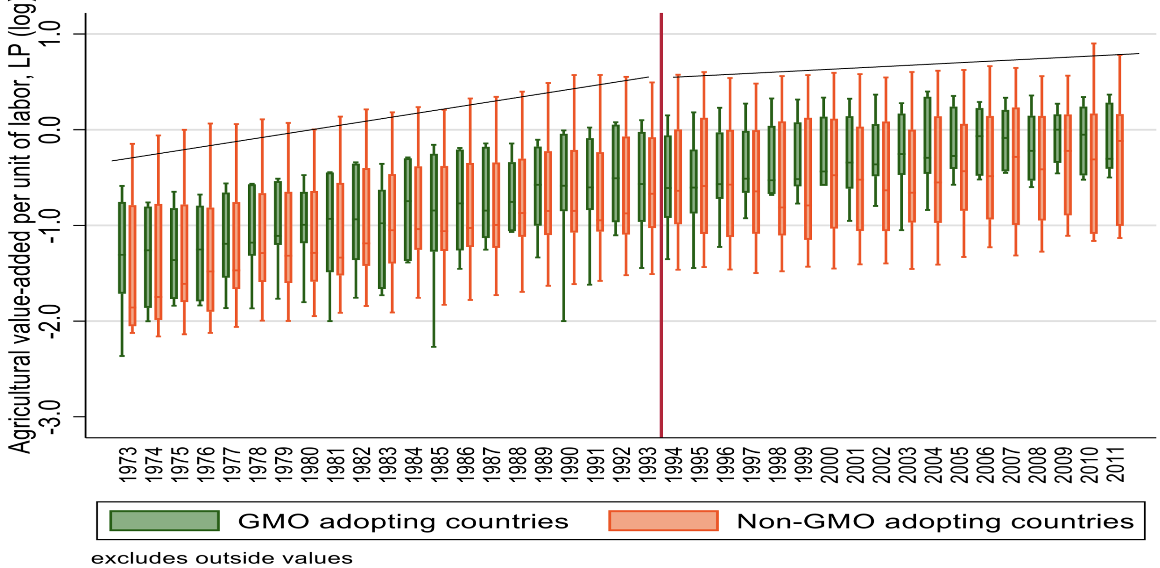
Table 1: **Summary statistics on LP and capital intensity segregated by GMO adoption strategy**

	$\ln y$	$\ln k$	Num. of Obs.
non-GMO adopting countries	-0.755	-1.582	351
	(0.739)	(0.699)	
GMO adopting countries	-0.628	-1.373	273
	(0.594)	(0.626)	
pre-GMO adoption period (GMO countries)	-1.060	-1.688	205
	(0.766)	(0.867)	
post-GMO adoption period (GMO countries)	-0.361	-1.313	107
	(0.619)	(0.626)	

Notes: Standard deviations are reported in parentheses.

Figure 3 presents the sample scatter diagram for $\ln y$ and $\ln k$. Red triangles denote observations for countries that eventually adopt GMO techniques and black dots non-GMO countries. The solid red curved represents the LOWESS smoothed regression plot for the GMO countries. The dotted black curve shows the smoothed regression plot for the non-GMO countries. Both smoothed plots exhibit a non-negative slope that decreases as capital intensity increases. At low capital-intensity levels, GMO countries exhibit a higher labor productivity than non-GMO countries. This tendency reverses itself at higher levels of capital

Figure 2: **Boxplot of the natural log of LP segregated by GMO adoption strategy**



Note: Sample outliers have been excluded for each year.

intensity. The data cloud formed by the red triangles appears to exhibit less dispersion and more severe diminishing returns to capital (or, K) than that formed by the black dots.

Figure 3: **Scatter and LOWESS smoothed regression between** lny **and** lnk **segregated by GMO adoption strategy**

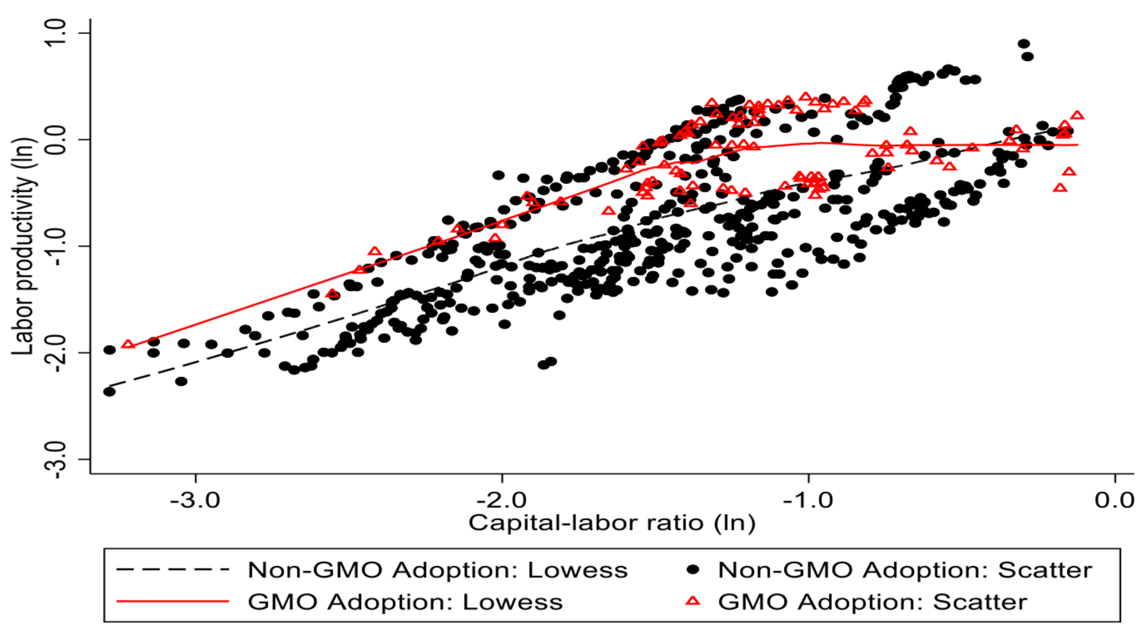


Table 2: **Estimated impact of GMO adoption on agricultural LP: OLS and 2SLS**

	All Sample	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Dependent variable: lny					
Constant	-0.987***	0.283	0.359	-	-
	(0.184)	(0.187)	(0.211)	-	-
b_0	-	0.787***	0.798***	0.755***	0.679***
	-	(0.082)	(0.082)	(0.224)	(0.216)
α	0.023	0.010	0.037	-0.239	-0.205
	(0.078)	(0.092)	(0.102)	(0.185)	(0.174)
β	-	-0.147**	-0.144**	-0.513***	-0.493***
	-	(0.051)	(0.053)	(0.167)	(0.152)
Number of Observations	585	585	453	453	453
R-squared	0.815	0.904	0.893	0.845	0.848
Number of countries	15	15	15	15	15

Notes: Robust standard errors in parentheses, and "$***$" $p < 0.01$, "$**$" $p < 0.05$, "$*$" $p < 0.1$.

Table 2 reports statistical estimates of b_0, α, and β obtained from the empirical specification:

$$\begin{aligned} \ln y_{it} - \overline{\ln y_{i\cdot}} &= v_t - \overline{v} + b_0 \left(\ln k_{it} - \overline{\ln k_{i\cdot}}\right) + \alpha \left(G_{it} - \overline{G_{i\cdot}}\right) \\ &+ \beta \left(G_{it} \ln k_{it} - \overline{G_{i\cdot} \ln k_{i\cdot}}\right) + \epsilon_{it} - \overline{\epsilon_{i\cdot}}, \end{aligned}$$

where $\overline{\ln y_{i\cdot}} = \frac{1}{T}\sum_t \ln y_{it}$, $\overline{\ln k_{i\cdot}} = \frac{1}{T}\sum_t \ln k_{it}$, $\overline{G_{i\cdot}} = \frac{1}{T}\sum_t G_{it}$, and $\overline{G_{i\cdot} \ln k_{i\cdot}} = \frac{1}{T}\sum_t G_{it} \ln k_{it}$. (Complete results for this specification are reported in Annex B.) The first column reports α estimated as the mean LP difference between GMO and non-GMO countries that accounts for country-specific and time-specific differences in AP. The estimated difference is positive but small, .02 log points, and imprecisely estimated.

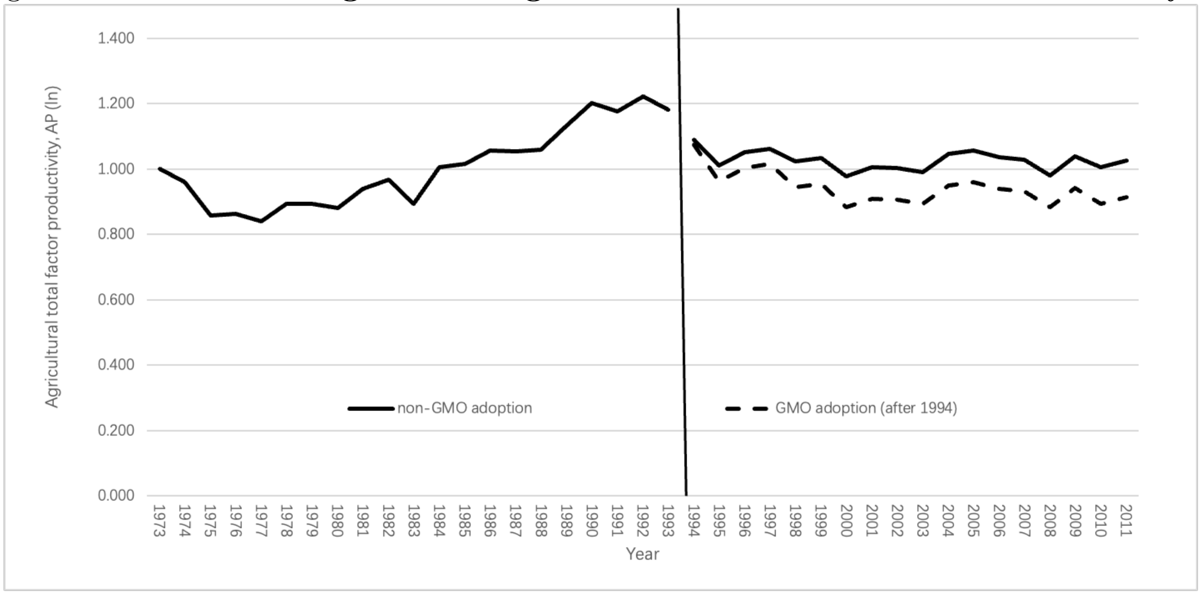
The second column reports OLS estimates of b_0, α, and β. The estimate for α is positive but even smaller than the mean-difference estimate and remains imprecisely estimated. The OLS estimate for β is negative, about -.15 log points, and statistically significant at the .05 confidence level.

Column 3 repeats the regression analysis summarized in Column 2 using a "matched sample" (see Annex A for details) instead of the entire 15 country panel. Column 4 reports parameters estimated using 2SLS in place of OLS applied to the matched sample (see Annex A), and Column 5 the 2SLS estimates obtained from the matched sample weighted to accommodate potential heteroskedasticity associated with different GMO adoption intensities across countries (see Annex A).

Although magnitudes differ, the qualitative regression results reported in Columns 3 to 5 are similar. Variation in capital intensity (k) is statistically significant in explaining LP variation across the original sample and the matched sample. Only the OLS estimate of α for the matched sample is positive. But it remains quite small, about .04 log points, and is imprecisely estimated. Both 2SLS estimates for α are negative, larger in absolute value terms, about -.24 to -.21, and more precisely estimated than the OLS estimate. Nevertheless, they remain insignificant at all traditional levels of confidence. The estimated β is uniformly negative for all three models and precisely estimated. The estimates from the 2SLS versions are roughly 3.5 times larger (in absolute value terms) than the OLS estimates.

In Annex B, we report parameter estimates for $v_t - \bar{v}$, each period's deviation from the time specific AP for the non-GMO technology. Setting $v_{1974} = 1$ gives an estimate of approximately 1.06 for $\bar{v}$ using either version of the 2SLS estimates. The $v_t - \bar{v}$ estimates are largely negative until circa 1985-1986 and positive (with some exceptions) thereafter. All estimates for the 2SLS versions are imprecise. The implication is that time-specific productivity differences grew steadily but slowly throughout the sample period. Figure 4 illustrates this pattern of AP growth using the 2SLS estimates from the matched but unweighted sample. (Before 1994 that growth pattern included all 15 OECD countries.) The solid curve is the non-GMO pattern, and the dotted segment that emanates from it illustrates inter-temporal AP growth pattern that would have occurred if GMO techniques had been adopted in 1994 (the United States was the earliest adopter). It suggests that GMO adopters would have experienced lower time-specific AP than adopters. (Recall, however, that the 2SLS α is not significantly different from zero.)

Figure 4: **Pattern of AP growth using the 2SLS estimate: Counterfactual analysis**



Robustness Checks

This section reports the results of several sensitivity analyses. Our first analysis is directed towards assessing the finding that GMO adoption is not accompanied by positive measurable gains in AP. To that end, we have used the same procedures described in the Data section to create a single aggregate input, call it X, from our K and L variates. Then, we calculated measured AP as value added per unit of X, Y/X. Measured AP was then used as the dependent variable in regression analyses that replicated those summarized in Table 2 after excluding lnk as an independent variable. The results for α are summarized in Table 3. The results are generally supportive of those reported in Table 2. The α estimate from OLS applied to the matched sample is positive and statistically different from zero at the .05 level. But the OLS analysis applied to the full sample for 15 countries produces a positive but imprecise estimate, while both 2SLS estimates for the matched sample are negative. For each of the estimated versions, the time-specific variates, $v_t - \bar{v}$ explained the bulk of the variation in AP.

To examine the inter-temporal behavior of the differences between the GMO and non-GMO technologies, we followed procedures developed by Autor (2003) and later used by

Table 3: **Estimated impact of GMO adoption on AP (measured as value-added, Y, per unit of X): OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: $lnAP$				
Constant	-1.402***	-1.293***	-	-
	(0.080)	(0.114)	-	-
α	0.142	0.175**	-0.045	-0.021
	(0.093)	(0.079)	(0.089)	(0.088)
Number of Observations	585	453	453	453
R-squared	0.733	0.72	0.686	0.698
Number of countries	15	15	15	15

Notes: In the first stage of 2SLS regression, we use the number of patents for GMO applied for in the previous 10 years as the instrument. Robust standard errors are in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Beck et al. (2010). We fitted regressions of the form

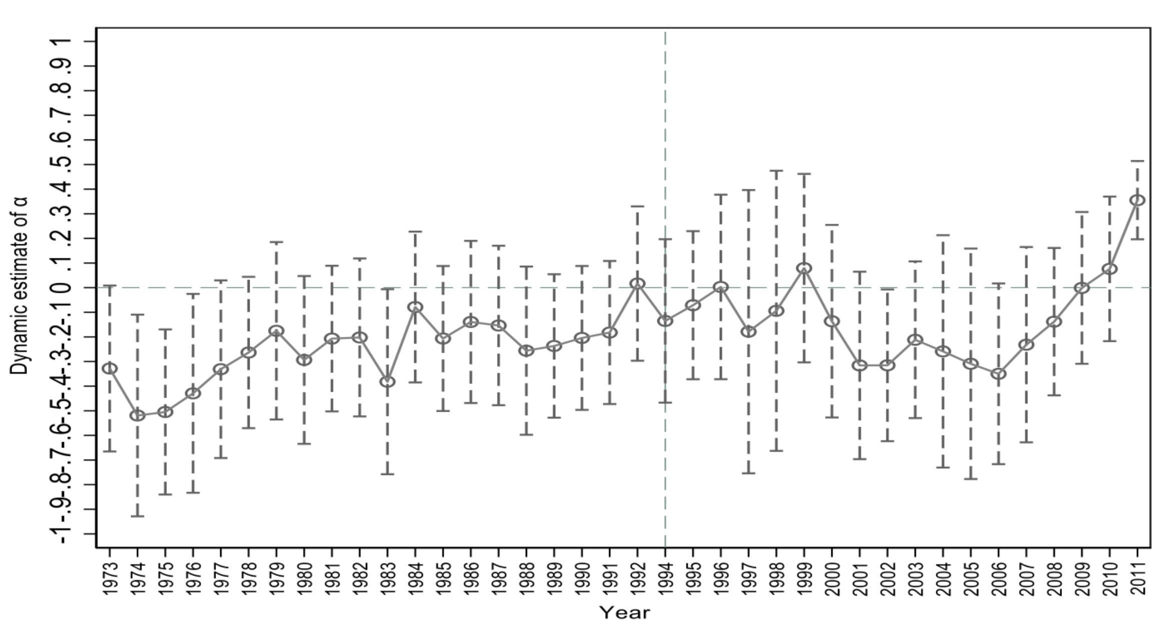
$$\begin{aligned} \ln y_{it} &= c_0 + u_i + v_t + b_0 lnk_{it} + \alpha_1 G_{it}^{-21} + \alpha_2 G_{it}^{-20} + ... + \alpha_{38} G_{it}^{+17} \\ &+ \beta_1 \left(G_{it}^{-21} \ln k_{it} \right) + \beta_2 \left(G_{it}^{-20} \ln k_{it} \right) + ... + \beta_{38} \left(G_{it}^{+17} \ln k_{it} \right) + \epsilon_{it}. \end{aligned}$$

Here G_{it}^{-j} equals one for country i in the jth year before it adopted the GMO technology and zero otherwise, and G_{it}^{+j} equals one for the jth year after GMO adoption and zero otherwise. The results are summarized in panels (a) and (b) of Figure 5. For all years except 2010 and 2011, the estimated coefficients, α_t, are not significantly different from zero at the .05 level. After 1994, they follow a pattern of being positive, then negative, and then returning to positive after 2007. The estimated coefficients, β_t, are consistently negative after 1994 and are statistically different from zero, with a few exceptions, after 2000.

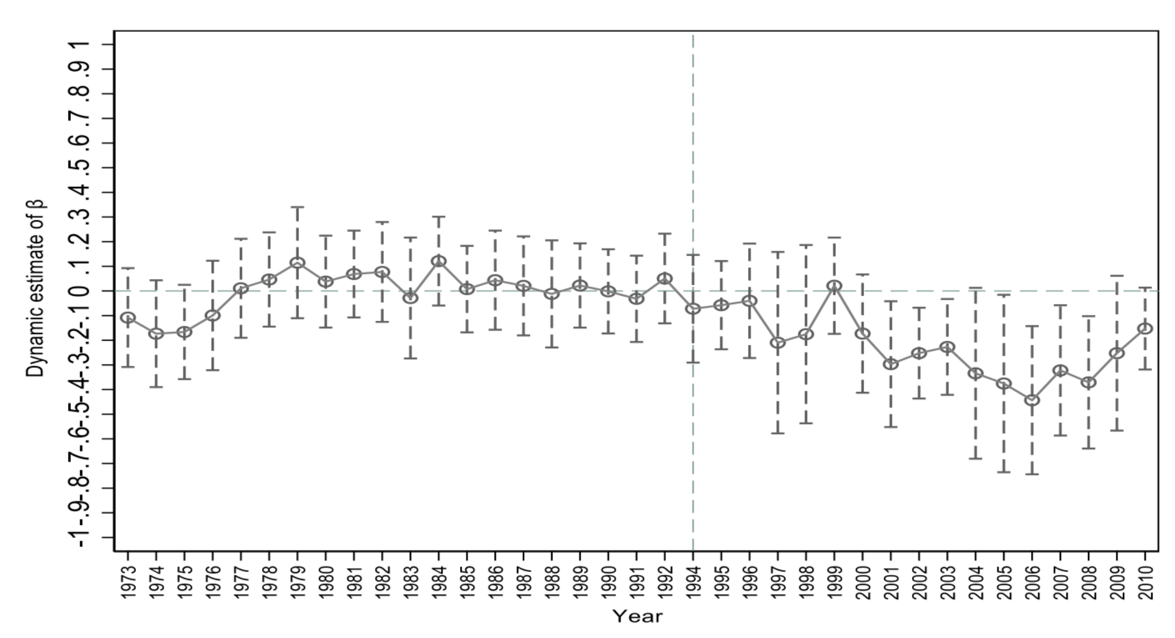
Finally, we also examined the impact of GMO adoption by making the counterfactual assumption that any country that eventually adopted GMO techniques did so in 1994. To examine this counterfactual assumption, we estimated the reformulated version of expression (2):

$$\ln y_{it} = c_0 + u_i + v_t + b_0 lnk_{it} + \alpha \hat{G}_{it} + \beta \hat{G}_{it} \ln k_{it} + \epsilon_{it}.$$

Figure 5: **Marginal impact of GMO adoption on agricultural LP**



(a) Estimated impact on AP (α) (95% confidence interval)



(b) Estimated impact on β (95% confidence interval)

Here $\hat{G}_{it} = 1$ for all GMO adoption countries after 1994 and zero otherwise. The results are summarized in Table 4. (More detailed results are reported in Annex B.) The estimated α's are both positive and negative, but again not statistically different from zero at traditional confidence levels. The estimated β's are all negative and significantly different from zero at the .10 level.

Table 4: **Estimated impact of GMO adoption on agricultural LP: Alternative GMO adoption strategy (1994)**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Dependent variable: lny				
Constant	-1.380***	0.282	0.382***	0.377***
	(0.076)	(0.178)	(0.093)	(0.092)
b_0'	-	0.782***	0.830***	0.825***
	-	(0.091)	(0.063)	(0.064)
α_0'	0.148	-0.037	0.103	0.11
	(0.121)	(0.132)	(0.099)	(0.100)
β_0'	-	-0.161*	-0.112*	-0.110*
	-	(0.088)	(0.062)	(0.063)
Number of Observations	585	585	453	453
R-squared	0.778	0.9	0.889	0.89
Number of countries	15	15	15	15

Notes: Robust standard errors are reported in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$. In the first stage of 2SLS regression, we use the number of patents for GMO applied for in the previous 10 years as the instrument.

Discussion

The empirical results suggest that GMO adopters experienced no AP gains after adoption and that GMO adoption enhanced the relative effectiveness of aggregate labor at the expense of aggregate capital. The absence of a positive GMO impact on AP and the hint that introducing GMOs lowered AP may seem surprising, especially given the micro-level evidence. Nevertheless, it is not unprecedented and echoes Solow's famous epigram that "You can see the computer age everywhere but in the productivity statistics."

The results reported here raise similar issues. What constitutes a technological revolution lies in the eye of the beholder. But our analysis reveals little to no evidence that adopting GMO techniques revolutionized agricultural productivity. What support there is that adopting GMO techniques enhances AP only occurs a decade and a half post adoption (see Figure 5a). Other studies using different data and different techniques have raised similar concerns, albeit in other contexts, for the United States, the international leader in adopting GMO techniques. Andersen, Alston, Pardey, and Smith (2018) concluded on the basis of an extensive time-series analysis of US agricultural total factor productivity performance that US agricultural productivity grew at an average annual rate of 1.16% over the period 1990-2007 as against an average annual rate of 1.42% over the 1910-1990 period. The last 14 years of that period overlap the post-GMO-adoption period for the United States, and the Andersen et al. (2018) estimated .26 decline is close to our 2SLS estimates of a .21 to .25 decline, despite the differences in data and techniques.[4] Similarly, in a study focused on the effects of climate change Ortiz-Bobea, Knippenberg, and Chambers (2018) using a state-level panel covering the period of 1960-2004, documented a slowing and increased dispersion of US agricultural productivity growth in the last decade of the 20th century. Neither the Andersen et al. (2018) study nor the Ortiz-Bobea et al. (2018) study used data that permitted comparisons between adopters and non-adopters of GMO techniques, but the overarching message of slowed agricultural productivity growth for the main adopter of GMO technology remains the same.

The story that emerges is that the most perceptible difference between GMO adopters and non-adopters is in how capital deepening affects LP. Capital deepening is less effective in promoting LP for GMO adopters than for non-adopters. For relatively labor rich countries, the implied increased marginal return to labor can enhance LP even if AP remains constant or declines. Six of the seven adopting countries adopted GMO techniques prior to 2001 (United States, Canada, Australia, France, Spain, and Germany). The seventh, Sweden, did so in 2010. Using our 2SLS results for the matched but unweighted sample, our point estimates of the average annual LP change associated with adopting GMO techniques for the 2000-2011 period are (expressed in log points): United States (.42), Canada (.70), Australia

[4]The 'productivity' measure used in Andersen et al. (2018) is multifactor productivity, which measures aggregate agricultural output per unit of an aggregate of all inputs, and not value added per unit of aggregated capital and labor.

(-.05), France (.26), Spain (.48), and Germany (.28).[5] Sweden adopted GMO techniques in 2010 and our point estimate of that adoption's impact on LP for 2011 is -.16. So, according to these estimates, roughly 28% of the GMO adopters experienced declines in both AP and LP.

Caselli (2005) suggests that raising developing countries agricultural LP to US levels might cause world income inequality to virtually disappear. The empirical result that countries with labor-rich agricultural sectors may enhance LP by adopting GMO techniques provides some support for the argument that widespread adoption of GMO techniques can help close that gap. While compelling, *caveats* exist. For example, the countries in our sample with the highest average LP are, in rank order, the Netherlands, Belgium, France, and the United States. Two non-adopters and non-adopters. In 1998 the year in which France adopted GMO techniques, its LP was approximately .78% of the Netherlands. In 2011, France's LP stood at 66% of the Netherlands. GMO adoption was accompanied by an increase and not a narrowing of the LP gap between France and the Netherlands. [6] It's also important to emphasize that the 15 countries in our panel also have far more productive agricultural sectors than the typical developing nation. Their agricultural sectors account for a small share of total GDP and employ a small portion of their labor force (Denmark with about 5% has the highest). How these empirical results extend to countries with very different capital structures and agricultural practices is problematic.

[5] All of these changes are calculated treating k for each time period as predetermined. These numbers measure difference in LP levels and not growth rates.

[6] Such numbers, of course, are always subject to "cherry picking". However, the Netherlands experienced a sharp drop in LP between 2010 and 2011, while France experienced an increase. If the same comparison were made for 2010, France's LP was approximately 56% of the Netherlands.

Annex A: Econometric Issues

Because our data are not drawn from a randomized trial, the potential for sample-selection bias exists. To accommodate it, we assume that: the data are consistent with the *conditional independence* or *unconfoundedness* condition that:

$$G \perp (\ln y | X)$$

where "$\perp$" denotes the independence relation between two random variables and X denotes a vector of covariates; and the probability of assignment to the GMO group versus the non-GMO group is bounded away from 0 and 1 given X, $Pr(G = 1|X) \in (0, 1)$. Our empirical representation of $Pr(G = 1|X) \in (0, 1)$ assumes a logit form where X consists of two covariates: the price of intermediate inputs used in agricultural production and per capita gross domestic production.

The estimated logit model is summarized in Annex Table A1. We use the estimated propensity scores to implement the propensity score matching technique to match GMO approved and non-approved countries described, for example, in Imbens and Rubin (2015, see in particular Sections 15.3, 15.3.3,18.4-5). Briefly, in each period for each country that has adopted GMO techniques we match it with the non-adopting country that is closest to it in terms of the distance between the linearized propensity scores. The matching process produces a "matched sample" with 453 observations. Parallel trend tests are reported in Annex Figure A1.

Because labor choice, capital choice, and GMO adoption may be affected by factors such as macroeconomic variates, macroeconomic shocks, attitudes towards GMOs and biotechnology not encompassed in our model, we use 2SLS procedure to accommodate the presence of missing explanatory factors. The instruments for the first-stage regressions are the relative price of intermediate inputs, the total number of GMO varieties created in a laboratory by a country in the preceding ten-year period before GMO technology has been first adopted, and the total number of GMO patent applications in the preceding ten years. The latter two variates are predetermined but also reflect a given country's attitudes towards GMO techniques. All three regressions were estimated in first-difference form using the OLS regression. The first-stage results are summarized in Annex Table A2.

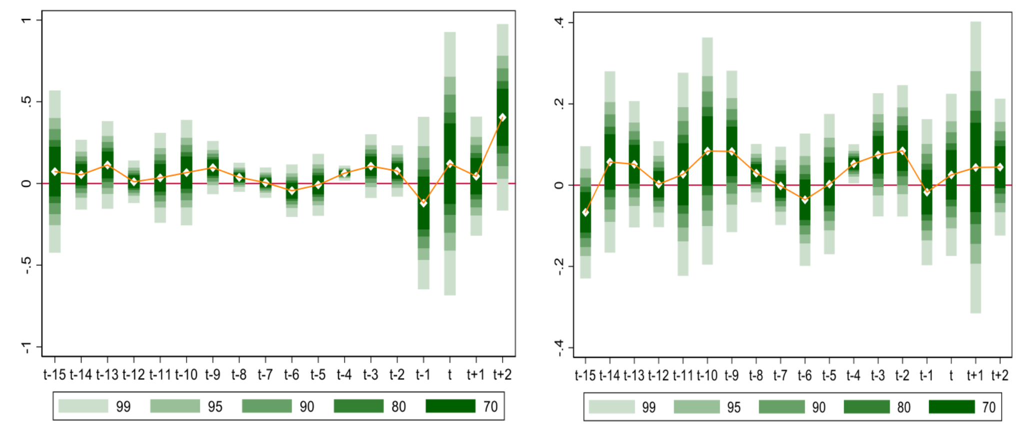
The intensity with which GMOs are adopted across countries varies. For example, the average GMO adoption intensity in the United States and Canada for the period of 1994-2011 are 45% and 22% respectively, while the adoption intensity for an EU adopter is less than 1%. Assigning equal weights to countries with different GMO adoption intensities in the regression analysis may bias the estimated impact of GMO adoption. To accommodate this problem, we use the exponential of GMO adoption intensity for each country to adjust the difference in GMO adoption intensity across countries.

Table A1: **First-stage logit model for the propensity score (PS) matching**

	Sub-sample (pre-1994)	All sample period
	(1)	(2)
Dependent variable: G_i		
GDP per capita (ln)	1.327**	0.464
	(0.567)	(0.439)
Relative price of intermediate inputs (US 1995=1)	-2.950***	-3.229***
	(0.573)	(0.442)
Constant	-11.597**	-2.953
	(5.704)	(4.412)
Year Dummies	Yes	Yes
LR Chi2(22)	47.45	69.57
Rseudo R-squared	0.109	0.086
Number of Observations	315	585

Notes: Robust standard errors in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Figure A1: **The parallel trend test for GMO adoption using the propensity score matched sample**



(a) Parallel trend test for Model(2) (b) Parallel trend test for Model(3)

Note: we use 15 periods lags and 6 periods leads in this parallel trend test, and the F-statistics are 1.79 (p-value 24.81%) and 1.93 (p-value 22.16%).

Table A2: **The first-stage regression results for the 2SLS models**

	Model (4) - PS			Model (5) – PS+Weight		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	lnk_{it}	G_{it}	$G_{it} * lnk_{it}$	lnk_{it}	G_{it}	$G_{it} * lnk_{it}$
Relative price of intermediate input	0.206***	0.311***	-0.101	0.187***	0.326***	-0.145
	(0.065)	(0.083)	(0.131)	(0.065)	(0.083)	(0.136)
number of GMO events (10 years ahead)	0.000	0.003***	-0.006***	0.000	0.002***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Number of patents applicants (10 years ahead)	0.000***	0.000**	0.000	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
interaction between GMO cty and lnkl	0.636***	0.430***	-0.050	0.645***	0.417***	-0.030
	(0.055)	(0.071)	(0.156)	(0.055)	(0.071)	(0.160)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-test of excluded instruments	13.88	28.59	18.52	13.07	27.74	18.26
Sanderson-Windmeijer multivariate F test	33.81	63.8	34.54	32.96	49.08	29.88
Kleibergen-Paap rk LM stat.		29.013			32.582	
Weak identification test		11.437			13.313	

Notes: Robust standard errors in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Annex B: Time-specific AP Change

In this section, we report the full set of estimates for those summarized in Table 2 (Annex Table B1) and Table 4 (Annex Table B2) in the text. Annex Figure B1 illustrates the time varying character of AP.

Table B1: **Estimated impact of GMO adoption on agricultural LP: OLS and 2SLS**

	All Sample	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Dependent variable: lny					
b_0	-	0.787***	0.798***	0.755***	0.679***
	-	(0.082)	(0.082)	(0.224)	(0.216)
α	0.023	0.010	0.037	-0.239	-0.205
	(0.078)	(0.092)	(0.102)	(0.185)	(0.174)
β	-	-0.147***	-0.144**	-0.513***	-0.493***
	-	(0.051)	(0.053)	(0.167)	(0.152)
Interaction between GMO Cty and lnk	0.417**	0.006	-0.009	0.102	0.159
	(0.190)	(0.114)	(0.129)	(0.184)	(0.194)
D_1974	0.011	-0.040*	-0.075*	-0.060	-0.052
	(0.031)	(0.022)	(0.042)	(0.126)	(0.126)
D_1975	0.056	-0.032	-0.127***	-0.163	-0.164
	(0.048)	(0.039)	(0.037)	(0.123)	(0.125)
D_1976	0.045	-0.068	-0.164***	-0.158	-0.147
	(0.065)	(0.061)	(0.048)	(0.125)	(0.124)
D_1977	0.112	-0.049	-0.149**	-0.179	-0.175
	(0.069)	(0.059)	(0.069)	(0.116)	(0.117)
D_1978	0.185**	-0.017	-0.095	-0.125	-0.117
	(0.083)	(0.060)	(0.074)	(0.110)	(0.109)
D_1979	0.203**	-0.027	-0.082	-0.125	-0.119
	(0.080)	(0.062)	(0.079)	(0.105)	(0.104)
D_1980	0.217**	-0.038	-0.111	-0.139	-0.129
	(0.089)	(0.070)	(0.090)	(0.112)	(0.112)
D_1981	0.244**	-0.008	-0.06	-0.08	-0.072
	(0.084)	(0.066)	(0.095)	(0.105)	(0.105)
D_1982	0.335***	0.049	-0.029	-0.052	-0.038
	(0.094)	(0.073)	(0.104)	(0.112)	(0.109)
D_1983	0.286**	-0.020	-0.087	-0.127	-0.113
	(0.113)	(0.079)	(0.109)	(0.118)	(0.115)
D_1984	0.417***	0.086	0.024	-0.013	-0.002
	(0.104)	(0.082)	(0.118)	(0.108)	(0.106)
D_1985	0.384***	0.068	0.015	-0.005	0.008
	(0.112)	(0.081)	(0.122)	(0.106)	(0.104)
D_1986	0.451***	0.103	0.073	0.037	0.054
	(0.105)	(0.078)	(0.115)	(0.118)	(0.114)
D_1987	0.487***	0.108	0.067	0.035	0.055
	(0.097)	(0.073)	(0.114)	(0.123)	(0.118)
D_1988	0.542***	0.134*	0.089	0.040	0.057
	(0.108)	(0.069)	(0.100)	(0.121)	(0.116)
D_1989	0.587***	0.193***	0.162	0.114	0.125
	(0.105)	(0.071)	(0.100)	(0.114)	(0.111)
D_1990	0.611***	0.222***	0.209**	0.181	0.194*
	(0.106)	(0.069)	(0.089)	(0.111)	(0.108)
D_1991	0.611***	0.201***	0.196**	0.155	0.171
	(0.092)	(0.063)	(0.085)	(0.118)	(0.114)
D_1992	0.675***	0.236***	0.238**	0.202	0.222*
	(0.087)	(0.072)	(0.104)	(0.128)	(0.122)
D_1993	0.692***	0.231***	0.212*	0.162	0.179
	(0.113)	(0.076)	(0.106)	(0.125)	(0.120)

Table B1 continued: **Estimated impact of GMO adoption on agricultural LP in full table: OLS and 2SLS**

	All Sample	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Dependent variable: lny					
D_1994	0.720***	0.230***	0.165	0.071	0.089
	(0.121)	(0.073)	(0.103)	(0.139)	(0.132)
D_1995	0.717***	0.198**	0.131	-0.009	0.009
	(0.139)	(0.080)	(0.111)	(0.163)	(0.155)
D_1996	0.743***	0.236***	0.168	0.031	0.048
	(0.118)	(0.078)	(0.112)	(0.150)	(0.143)
D_1997	0.755***	0.240***	0.172	0.043	0.058
	(0.108)	(0.078)	(0.116)	(0.145)	(0.139)
D_1998	0.767***	0.231***	0.161	0.004	0.018
	(0.097)	(0.072)	(0.106)	(0.150)	(0.142)
D_1999	0.782***	0.238***	0.167	0.014	0.028
	(0.102)	(0.073)	(0.107)	(0.151)	(0.144)
D_2000	0.800***	0.217**	0.144	-0.041	-0.026
	(0.138)	(0.090)	(0.127)	(0.157)	(0.152)
D_2001	0.818***	0.220***	0.148	-0.015	0.003
	(0.125)	(0.081)	(0.116)	(0.160)	(0.151)
D_2002	0.811***	0.212**	0.139	-0.017	-0.001
	(0.126)	(0.090)	(0.121)	(0.158)	(0.149)
D_2003	0.803***	0.204**	0.132	-0.030	-0.011
	(0.122)	(0.092)	(0.123)	(0.159)	(0.151)
D_2004	0.873***	0.251***	0.178	0.027	0.051
	(0.126)	(0.096)	(0.129)	(0.163)	(0.154)
D_2005	0.905***	0.244**	0.171	0.037	0.064
	(0.134)	(0.099)	(0.124)	(0.168)	(0.159)
D_2006	0.886***	0.213**	0.140	0.016	0.045
	(0.130)	(0.094)	(0.122)	(0.167)	(0.157)
D_2007	0.912***	0.203**	0.13	0.008	0.041
	(0.147)	(0.091)	(0.124)	(0.175)	(0.164)
D_2008	0.873***	0.166	0.092	-0.04	-0.011
	(0.144)	(0.106)	(0.133)	(0.177)	(0.166)
D_2009	0.956***	0.207**	0.133	0.019	0.052
	(0.154)	(0.103)	(0.130)	(0.183)	(0.170)
D_2010	0.903***	0.161*	0.086	-0.014	0.024
	(0.147)	(0.094)	(0.124)	(0.174)	(0.164)
D_2011	0.943***	0.183*	0.107	0.006	0.041
	(0.167)	(0.107)	(0.133)	(0.180)	(0.169)
Constant	-0.987***	0.283	0.359	-	-
	(0.184)	(0.187)	(0.211)	-	-
Number of Observations	585	585	453	453	453
R-squared	0.815	0.904	0.893	0.845	0.848
Number of countries	15	15	15	15	15

Notes: Robust standard errors in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Figure B1: **Time specific AP effects of non-GMO adopting countries**

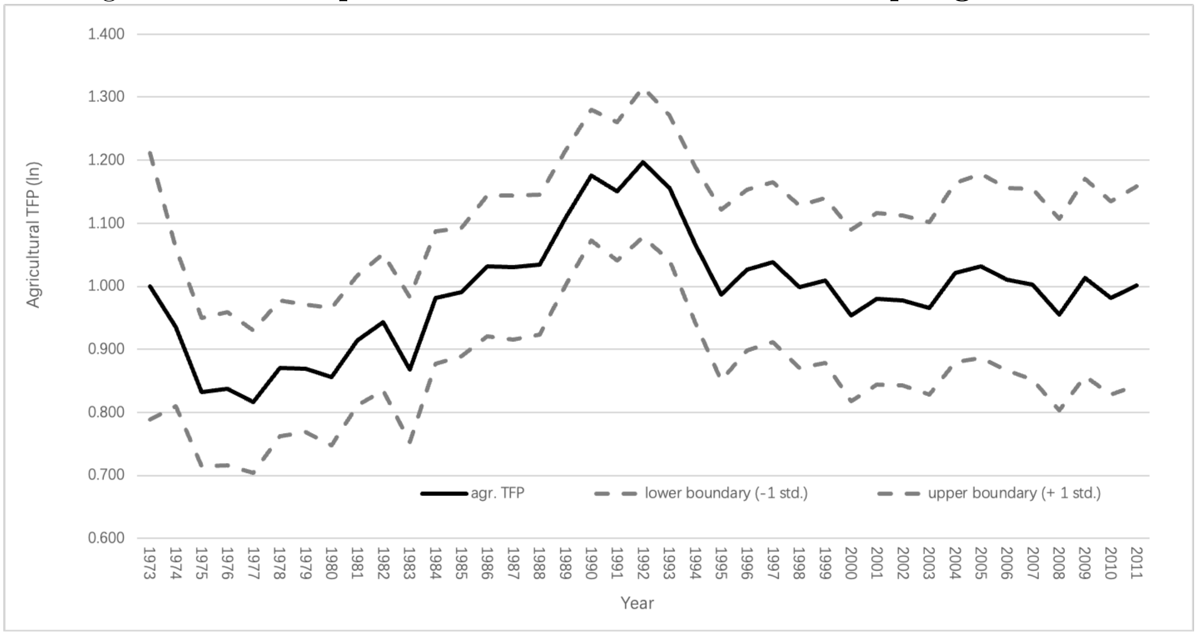


Table B2: **Estimated impact of GMO adoption on AP (measured by using value-added, Y, divided by X) in full table: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: : *lnAP*				
Constant	-1.402***	-1.293***	-	-
	(0.080)	(0.114)	-	-
α	0.142	0.175**	-0.045	-0.021
	(0.093)	(0.079)	(0.089)	(0.088)
D_1974	0.025	-0.029	-0.043	-0.043
	(0.034)	(0.056)	(0.154)	(0.148)
D_1975	0.059	-0.054	-0.031	-0.032
	(0.052)	(0.084)	(0.140)	(0.136)
D_1976	0.040	-0.067	-0.081	-0.078
	(0.073)	(0.079)	(0.136)	(0.131)
D_1977	0.094	-0.021	-0.009	-0.008
	(0.073)	(0.092)	(0.124)	(0.120)
D_1978	0.149*	0.045	0.055	0.053
	(0.085)	(0.105)	(0.121)	(0.117)
D_1979	0.182**	0.112	0.131	0.128
	(0.081)	(0.104)	(0.118)	(0.114)
D_1980	0.207**	0.104	0.104	0.100
	(0.086)	(0.119)	(0.127)	(0.124)
D_1981	0.237***	0.141	0.141	0.143
	(0.075)	(0.099)	(0.126)	(0.123)
D_1982	0.321***	0.236**	0.236*	0.235**
	(0.081)	(0.100)	(0.123)	(0.120)
D_1983	0.251**	0.189	0.208	0.200
	(0.097)	(0.125)	(0.144)	(0.141)
D_1984	0.382***	0.267**	0.276**	0.276**
	(0.088)	(0.117)	(0.122)	(0.119)
D_1985	0.376***	0.299**	0.297**	0.298**
	(0.089)	(0.119)	(0.125)	(0.123)
D_1986	0.429***	0.395***	0.405***	0.403***
	(0.093)	(0.132)	(0.125)	(0.121)
D_1987	0.461***	0.413***	0.414***	0.415***
	(0.087)	(0.126)	(0.113)	(0.110)
D_1988	0.505***	0.431***	0.449***	0.445***
	(0.092)	(0.127)	(0.116)	(0.113)
D_1989	0.558***	0.471***	0.489***	0.487***
	(0.090)	(0.125)	(0.113)	(0.110)
D_1990	0.591***	0.526***	0.526***	0.525***
	(0.081)	(0.104)	(0.119)	(0.116)
D_1991	0.572***	0.538***	0.547***	0.545***
	(0.072)	(0.098)	(0.114)	(0.112)

Table B2 continued: **Estimated impact of GMO adoption on AP (measured by using value-added, Y, divided by X) in full table: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: $lnAP$				
D_1992	0.621***	0.600***	0.598***	0.600***
	(0.071)	(0.104)	(0.114)	(0.111)
D_1993	0.629***	0.571***	0.589***	0.587***
	(0.083)	(0.114)	(0.114)	(0.111)
D_1994	0.635***	0.537***	0.601***	0.596***
	(0.091)	(0.118)	(0.118)	(0.115)
D_1995	0.621***	0.518***	0.612***	0.601***
	(0.098)	(0.115)	(0.123)	(0.121)
D_1996	0.658***	0.555***	0.649***	0.640***
	(0.091)	(0.117)	(0.120)	(0.118)
D_1997	0.665***	0.563***	0.657***	0.649***
	(0.089)	(0.119)	(0.121)	(0.119)
D_1998	0.660***	0.554***	0.677***	0.667***
	(0.079)	(0.115)	(0.128)	(0.126)
D_1999	0.676***	0.569***	0.692***	0.683***
	(0.083)	(0.118)	(0.131)	(0.129)
D_2000	0.677***	0.568***	0.706***	0.692***
	(0.100)	(0.118)	(0.132)	(0.131)
D_2001	0.683***	0.574***	0.712***	0.700***
	(0.096)	(0.117)	(0.129)	(0.127)
D_2002	0.679***	0.569***	0.708***	0.695***
	(0.100)	(0.127)	(0.132)	(0.130)
D_2003	0.669***	0.560***	0.698***	0.687***
	(0.100)	(0.130)	(0.135)	(0.133)
D_2004	0.732***	0.622***	0.761***	0.750***
	(0.100)	(0.129)	(0.131)	(0.129)
D_2005	0.745***	0.636***	0.774***	0.764***
	(0.108)	(0.135)	(0.137)	(0.135)
D_2006	0.723***	0.614***	0.752***	0.742***
	(0.106)	(0.133)	(0.134)	(0.133)
D_2007	0.734***	0.625***	0.763***	0.753***
	(0.117)	(0.139)	(0.136)	(0.135)
D_2008	0.689***	0.580***	0.718***	0.707***
	(0.114)	(0.139)	(0.133)	(0.132)
D_2009	0.745***	0.636***	0.774***	0.763***
	(0.120)	(0.140)	(0.138)	(0.137)

Table B2 continued: **Estimated impact of GMO adoption on AP (measured by using value-added, Y, divided by X) in full table: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: $lnAP$				
D_2010	0.690***	0.578***	0.731***	0.720***
	(0.121)	(0.140)	(0.140)	(0.139)
D_2011	0.730***	0.619***	0.772***	0.759***
	(0.123)	(0.131)	(0.137)	(0.135)
Number of Observations	585	453	453	453
R-squared	0.733	0.72	0.686	0.698
Number of countries	15	15	15	15

Notes: In all models, we controlled the interaction term between G_i and lnk_{it}, as well as u_i and v_t. Robust standard errors in parentheses, and "$***$" $p < 0.01$, "$**$" $p < 0.05$, "$*$" $p < 0.1$.

References

T. Adamopoulos and D. Restuccia. The size distribution of farms and international productivity differences. American Economic Review, 104(6):1667–97, 2014.

M. A. Andersen, J. M. Alston, P. G. Pardey, and A. Smith. A century of us farm productivity growth: A surge then a slowdown. American Journal of Agricultural Economics, 100(4): 1072–1090, 2018.

D. H. Autor. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. Journal of Labor Economics, 21(1):1–42, 2003.

J. Bailey-Serres, J. E. Parker, E. A. Ainsworth, G. E. Oldroyd, and J. I. Schroeder. Genetic strategies for improving crop yields. Nature, 575(7781):109–118, 2019.

V. E. Ball, J.-C. Bureau, J.-P. Butault, and R. Nehring. Levels of farm sector productivity: An international comparison. Journal of Productivity Analysis, 15(1):5–29, 2001.

V. E. Ball, W. Lindamood, R. Nehring, and C. S. J. Mesonada. Capital as a factor of production in oecd agriculture: Measurement and data. Applied Economics, 40(10):1253–1277, 2008.

V. E. Ball, J.-P. Butault, C. S. Juan, and R. Mora. Productivity and international competitiveness of agriculture in the european union and the united states. Agricultural Economics, 41(6):611–627, 2010.

T. Beck, R. Levine, and A. Levkov. Big bad banks? the winners and losers from bank deregulation in the united states. The Journal of Finance, 65(5):1637–1667, 2010.

F. Caselli. Accounting for cross-country income differences. Handbook of Economic Growth, 1:679–741, 2005.

Y. Eshed and Z. B. Lippman. Revolutions in agriculture chart a course for targeted breeding of old and new crops. Science, 366(6466):eaax0025, 2019.

G. W. Imbens and D. B. Rubin. Causal inference in statistics, social, and biomedical sciences. Cambridge University Press, 2015.

ISAAA. Global status of commercialized biotech/gm crops in 2019: Biotech crops drive socio- economic development and sustainable environment in the new frontier. Brief 55, ISAAA, Ithaca, NY., 2019.

D. Lagakos and M. E. Waugh. Selection, agriculture, and cross-country productivity differences. American Economic Review, 103(2):948–80, 2013.

A. Ortiz-Bobea, E. Knippenberg, and R. G. Chambers. Growing climatic sensitivity of us agriculture linked to technological change and regional specialization. Science Advances, 4(12):eaat4343, 2018.

D. Restuccia, D. T. Yang, and X. Zhu. Agriculture and aggregate productivity: A quantitative cross-country analysis. Journal of Monetary Economics, 55(2):234–250, 2008.

Y. Sheng, E. Ball, K. Nossal, et al. Comparing agricultural total factor productivity between australia, canada, and the united states, 1961-2006. International Productivity Monitor, 29:38–59, 2015.

T. Wheeler and J. Von Braun. Climate change impacts on global food security. Science, 341 (6145):508–513, 2013.

S. S.-e.-A. Zaidi, H. Vanderschuren, M. Qaim, M. M. Mahfouz, A. Kohli, S. Mansoor, and M. Tester. New plant breeding technologies for food security. Science, 363(6434):1390–1391, 2019.