Genetically Modified Organisms and Agricultural Productivity[1]

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Abstract

We use newly developed agricultural production account data comparable across 15 OECD countries (1973-2016) to study the impact of adopting agricultural production techniques that incorporate genetically modified organisms on a nation's aggregate agricultural productivity. We first develop and estimate a neoclassical production accounting framework for agriculture that distinguishes between GMO and non-GMO agricultural production processes. Exogenous variation of crop-specific pest shocks in geography, combined with the timing of technology innovation in a difference-in-difference strategy, is used to identify GMO adoption by countries. Then we follow with a series of robustness checks. The evidence suggests that the impact on aggregate total factor productivity is small to nonexistent and that the main impact of GMO adoption is to decrease the effectiveness of capital deepening in promoting labor productivity growth.

Key words: GMOs, agricultural labor productivity, capital deepening, TFP

Introduction

Recent years have witnessed an increased interest in better understanding the nexus between technological progress and long-term agricultural productivity growth (Caselli 2005; Gollin et al. 2007; Restuccia et al. 2008; Adamopolous 2011; Lagakos and Waugh 2013; Gollin et al. 2013, 2014; Adamopoulos and Restuccia 2014; Tombe 2015; Tombe 2015; Duncan et al. 2021). A protracted slowdown in agricultural productivity growth and an associated growing productivity gap across countries have heightened concerns about global food security. This decline in agricultural productivity growth has been attributed, among other causes, to worsening climate conditions, a deteriorated natural resource base and ecological system, and reduced public investment in agricultural research and development (Alston, Andersen and Pardey 2015; Ortiz-Bobea et al. 2018). Emerging studies suggest, however, that biotechnological innovations in the form of genetically modified organisms (GMO) might revolutionize agriculture and restore its productivity growth (Wheeler and Von Braun 2013; Bailey-Serres et al. 2019; Eshed and Lippman 2019; Zaidi et al. 2019).

Little empirical evidence exists, however, on the effects that GMO techniques have on sector-level agricultural productivity performance. Existing evidence, instead, comes mainly from laboratory experiments, farm-level studies, and regional-level studies that suggest GMO techniques can reduce the gap between actual and potential crop yields (Fernandez-Cornejo et al. Fernandez-Cornejo et al.; Klümper and Qaim 2014). But contemporaneous aggregate and cross-country comparisons report little, or even negative, yield effects in many developed countries (NASEM 2016; Scheitrum et al. 2020; Hansen and Wingender 2023b).

Explanations for small yield response to GMOs have yet to emerge. It may be that selection and equilibrating adjustments associated with GMO adoption may limit sector-level impacts as labor, capital, and other resources are diverted to other tasks within the agricultural sector. Moreover, many GMO techniques, such as Bt cotton and Roundup Ready© soybeans are designed to control pest damage and may not enhance potential yield and productivity in the absence of significant pest and weed pressure.

We use a newly developed data set for 15 OECD countries for the 1973-2016 period to study the impact that GMO techniques have on aggregate agricultural productivity. We develop a simple structural model that distinguishes the impact of adopting GMO techniques on aggregate agricultural productivity from that of capital deepening. Our identification strategy combines exogenous geographical agro-climatic and ecological variation with time variation of technological progress using a difference-in-difference strategy. We find little to no empirical evidence that commercializing GMO techniques had a significant effect on total factor productivity in agriculture, but those techniques do seem to improve labor productivity in agriculture. We speculate that using GMO techniques may reduce the need for labor-intensive tasks such as weeding and pesticide application thus improving labor productivity.

A large literature studies the social, economic, and environmental impact of GMO adoption.[1] It would be overly ambitious for us to summarize it all. But we can highlight three strands that relate closely to our study. Our paper addresses similar macroeconomic issues as those Barrows et al. (2014), Scheitrum et al. (2020) and Hansen and Wingender (2023b) study.[2] Although cast at a macro level, these studies focus on partial productivity measures such as crop yield, harvest area, and labor intensity. Our analysis instead targets agricultural total factor productivity measures based on national account statistics that attempt to account properly for all inputs and outputs.

Our paper also uses agro-ecological variation and time variation arising from technological progress to create instruments for GMO adoption. Similar empirical strategies were used to examine the impacts of adopting gene-modified maize/soybean (Bustos and Ponticelli 2022) and the economic impact of adopting Green-Revolution high-yield varieties (Gollin et al. 2021). While those studies used potential yield measures based on agro-climatic conditions, we use exogenous geographical variation in pest shocks to create instruments for cross-region variation. Pest shocks are more relevant to our study because most GMO varieties are designed to be pest or pesticide resistant. Consequently, they only promise higher yields in the presence of significant pest pressure.

Our paper also relates to the literature that investigates the role of biotechnological innovation in agricultural transformation and economic development. This literature includes,

[1] Recent economic surveys include Carpenter (2010), Klümper and Qaim (2014) and NASEM (2016).

[2] There are also some recent studies focused on region-level impact of GMO adoption within a single country. See Bustos and Ponticelli (2022) for Brazil, Hendricks et al. (2019) and Lusk et al. (2018) for the United States.

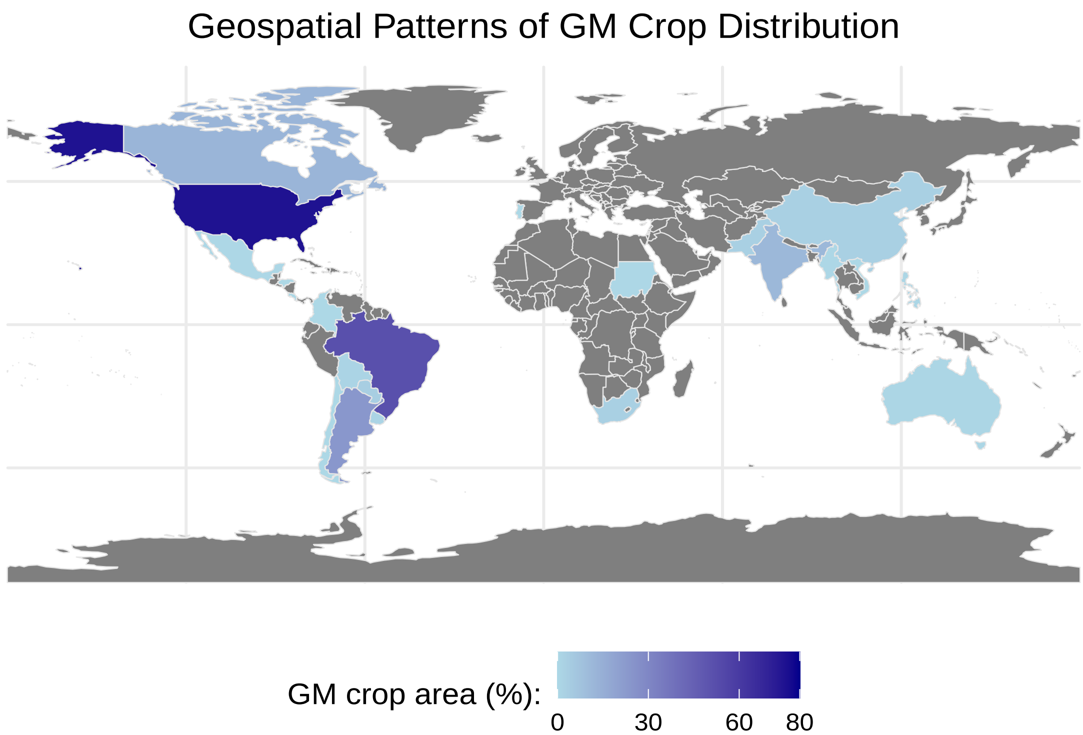
among others, the classic work of Olmstead and Rhode (1993, 2008) and the more recent Bustos and Ponticelli (2022) and Gollin et al. (2013, 2021). The latter show that the adoption of high yield and GMO varieties promoted capital intensive technology progress. Our paper adds to this literature by providing additional evidence that GMO technologies will increase the efficiency of labor input in agricultural production from a cross-country comparison perspective.

The paper proceeds as follows. We first present an overview of the pattern of GMO adoption. Next we introduce a simple macroeconomic productivity accounting framework that distinguishes between GMO and non-GMO agricultural production processes. We then discuss our data and present the estimation results. An examination of a series of robustness checks for the estimated model follows, and the paper then closes with a discussion of the how our works contributes to existing knowledge of GMOs and agricultural performance.

GMO Adoption in OECD Countries

GMOs are organisms into which gene coding for desirable traits has been inserted (Qaim 2009). It can promote particular traits that include lower chemical fertilizer and pesticide needs and better pest resistance. Since 1992, when gene-modified tobacco was introduced, many new GMO techniques have appeared, and by 2019 the global area sown to genetically modified varieties reached approximately 18% of arable land (190 million hectares distributed across 29 countries, see Figure 1).

Figure 1: Geographic Distribution of GMO adopting Countries: 2016



Note: The darkness of the colour represents GMO adoption intensity, defined as the ratio of GMO planting area in total crop sowing area.

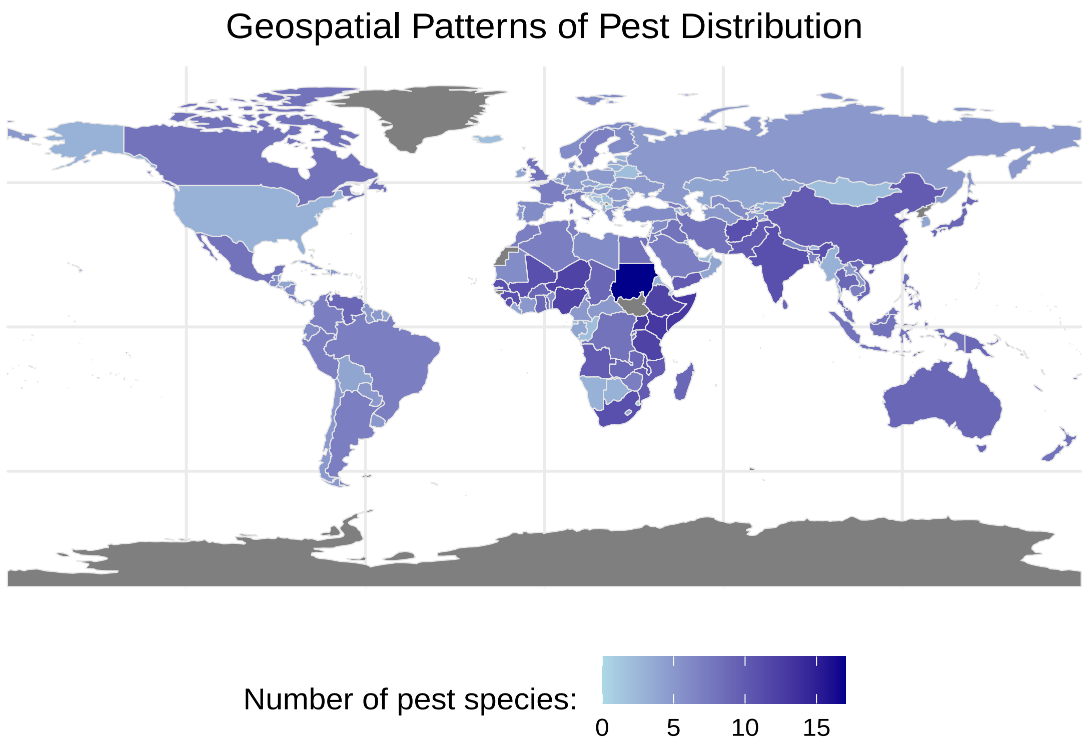
Source: The data are from GMO approval database (ISAAA 2019), available online at

http://www.agropages.com/AgroData/

The United States, Canada, and Australia introduced GMO techniques in the mid 1990s, but other OECD countries have not widely adopted them. For example, most EU countries still ban cultivation of GMO crops even though they have invested large sums in public and private GMO-related research and development and allow imports of GMO related commodities. As of 2019, only 10 out of the 26 OECD countries had approved the commercial use of GMO varieties. The total OECD area grown with GMO crops accounted for approximately

8% of its total arable land (84 million hectares) in 2019. And since 2011, OECD adoption of GMO technologies has lagged behind that in developing countries.

Figure 2: Geographical Distribution of Average Crop Pests



Note: The darkness of the colour represents seriousness of the pest shock.

Source: The data are obtained from the CABI databased on crop pest compendium, which are compiled based on experts' review on outbreak of crop pest using the published literature in plant pathology and agronomy. Please refer to Moscona and Sastry (2022) for the more detailed method used to compile the data.

GMO methods often do not promise to increase conventional crop yields when grown under ideal conditions. Instead, GMO innovations are often meant to control weeds and other pests while using less labor, chemicals, and other intermediate inputs. Figure 2 shows the geographical distribution of average crop pests across countries. Not surprisingly, it is positively correlated with GMO adoption intensity. This may help explain why macroeconomic studies find little evidence adopting GMO techniques enhances crop yield growth, in developed countries (NASEM 2016; Lusk et al.2018; Hansen and Wingender 2023b.

The Model

We assume that aggregate agricultural value added, Y, is a function of aggregate agricultural capital, K, and aggregate agricultural labor, L:[3]

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

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.[4]

[3]The assumption that aggregate agricultural production is characterized by an aggregate production function is strong, but it is consistently maintained in the macroeconomic and development productivity literature.

[4]Our data on capital and labor were constructed using hedonic adjustments over time and other dimensions to accommodate non-neutral technical differences. 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 literature, which focus on returns to aggregate capital 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 total factor (multifactor) productivity is gross agricultural output (and not value added) divided by total agricultural input use. To prevent confusion, we use the AP terminology.

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 production process and by

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

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 a GMO and non-GMO process on how capital deepening affects labor-productivity growth.

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 (efficiency) differences, v_t is a time-specific AP effect that controls for time-varying productivity differences (technical change), and ϵ_{it} is a white-noise, productivity error component.

The Data

The data are for 15 OECD countries for the period of 1973-2016.[5] These data extend data sets detailed in Ball et al. (2001, 2010) and Sheng et al. (2015). We describe the data used to

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

construct agricultural production accounts and the key variables for these OECD countries in Annex A.[6] The agricultural production 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) aggregated from the commodity-level data. An important feature of the data set is that it makes agricultural inputs and outputs consistently comparable across countries in a national accounting system framework with an appropriate accounting for quality differences in capital (which includes land) and labor 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, labor and capital. Other inputs are aggregated into a single factor, 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 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

[6] Interested readers can also refer to the public release of dataset on the website: https://icapproject.com/

assumptions to model variations in actual 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 26 land characteristics (or quality) and their change over time based on the data of more than 3500 states/regions. This treatment incorporates important, but difficult to measure factors, such as environmental endowments, natural resource endowments, and soil characteristics into the capital measure.

We measure GMO adoption by constructing a time-varying dummy for each country using the data on GMO approval events from International Services for the Acquisition of Agri-biotech Application (ISAAA 2019).[7] The dummy variable takes the value one in a country for each year after the first GMO event has been commercially adopted and zero otherwise. Between 1973 and 2016, 7 out of the 15 countries studied approved GMO commercial use. They are the United States (1994), Canada (1995), Australia (1995), Spain (1998), France (1998), Germany (2000), and Sweden (2010). [8] Additionally, we also use GMO adoption intensity, defined as GMO cropping areas divided by the total cropping area, as an alternative measure of GMO adoption. We treat the dummy for GMO approval as a preferred measure for GMO adoption because of two reasons. One reason is that the measure is more consistent with our theoretical framework as the dummy for GMO approval represents an external shock.[9] The other reason is that using the dummy for GMO approval

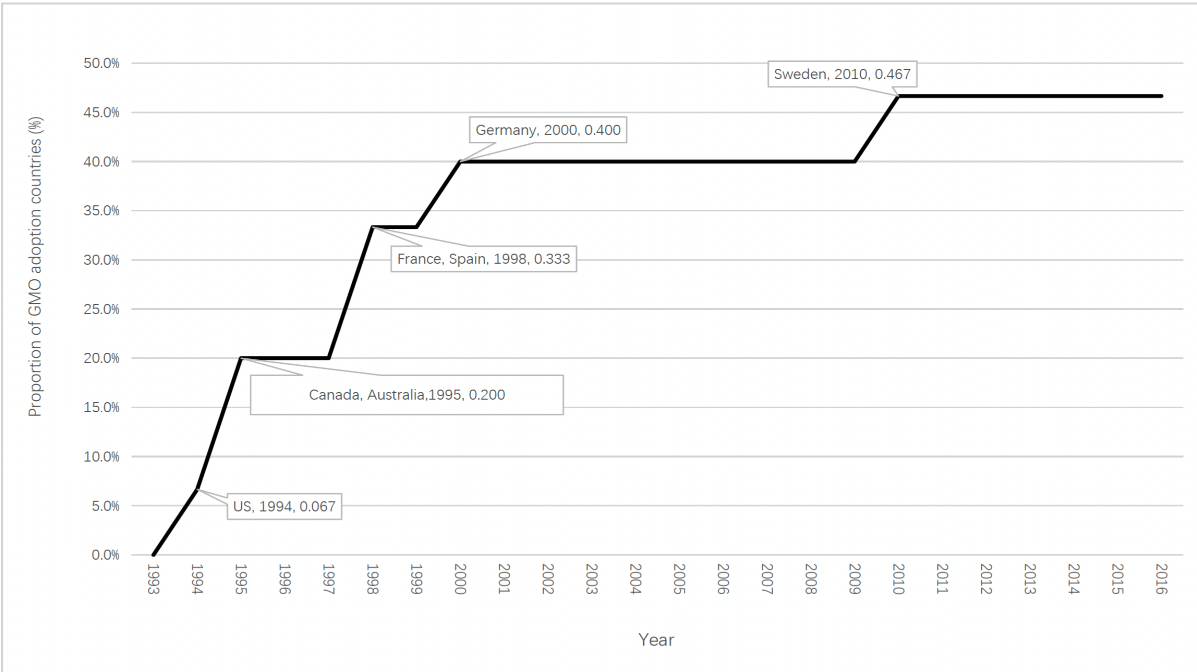
[7]We only include field crops in our analysis, whereby we exclude GMO varieties of a few specialty crops, such as eggplant and papaya. This is no severe limitation, as cotton, maize, soybean and canola account for more than 98 % of global GMO crop in commercialization.

[8]Considering that France and Germany have stopped the use of GMOs in field in 2008 and 2012, we also define another dummy variables that allow the two countries to be in the control group either after they disapproved GMOs or for the whole period to account for the impact of their exiting from GMO adoption countries as robustness checks

[9]The commercial approval of GMO use is usually the result of a complex socio-economic process that balances public concerns about its safety (and related regulatory hurdles for their commercialization) and industrial support for adoption.

helps to avoid the measurement problem caused by inaccurate statistics on the planting area of GMO crops. Figure 3 illustrates the GMO adoption time line.

Figure 3: 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/.

Finally, we measure the pest shock (as the key instrumental variable) by using the presence of crop-specific pests and pathogens (CPPs) based on the data on the global distribution and host-plant specificity of all known CPPs, including viruses, bacteria, parasitic plants, insects and fungi. They are estimated to reduce annual global agricultural output by 50-80 % (Oerke and Dehne 2004), and CPP resistance has been a key focus of GMO technology development. The measure is compiled by Moscona and Sastry (2022) using expert reviews of published literature in plant pathology and agronomy, which reflects the global distribution of plant ecosystem threats in ecological sciences (Dong and Ronald 2019). Other variables in use are described in Appendix B.

Econometric Issues and Estimation Strategies

In estimating the structural model, we face a number of econometric challenges. First, GMO adoption is not randomly assigned across countries, which raises the potential for sample-selection issues. Second, a country's decision on GMO adoption, its capital investment and labor allocation, likely depend on common macroeconomic factors, public attitudes, and other variables not included in our model. Without a proper identification strategy, our estimates may suffer from omitted-variable or reverse-causality problems. Third, GMO adoption across countries varies over time, making it difficult to compare its effect between the pre- and post- adoption periods. Without properly accounting for these time-varying GMO adoption shocks, conventional estimation methods are not guaranteed to yield interpretable causal parameters. Fourth, some countries, France and Germany, revoked GMO approval after initially granting it. Ignoring such behaviour could contaminate the estimated effects of GMO adoption. Finally, countries adopted GMO techniques with different intensities at different time periods.

This section discusses an estimation strategy to address these econometric issues.[10] Our first step is to construct a common support sample. Because our data are not drawn from a randomized trial, the potential for sample-selection bias exists between GMO-adopting and non-adopting countries. To accommodate it, we assume that the probability of assignment to the GMO group versus the non-GMO group is bounded away from 0 and 1 given X, $Pr(G = 1|X) \in (0, 1)$; and that the data are consistent with the *conditional independence* condition that $G \perp (\ln y|X)$, where "$\perp$" denotes the independence relation between two random variables and X denotes a vector of covariates.

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 (GDP). Using the price of intermediate inputs to help identify a country's choice of GMO adoption is reasonable because we work in value-added framework and GMO adoption usually involves herbicide-tolerant and insect/bacteria-resistant varieties that are correlated with the use of intermediate inputs such as herbicides

[10]Please refer to Annex B for a more detailed discussion on the related econometric results.

and pesticides. Per capita GDP captures a country's income and research capacity and public awareness of biotechnology, but it will not directly affect agricultural LP and AP.

The estimated logit model is summarized in Annex Table B1. We use the estimated propensity scores described, for example, in Imbens and Rubin (2015, see in particular Sections 15.3, 15.3.3,18.4-5) to implement the one-to-one propensity score matching technique to match GMO adopting and non-adopting countries in 1993 immediately before the first GMO variety has been commercialized in the United States. Briefly, in that 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 403 observations. A set of parallel trend tests for both the full sample and the "matched sample" are conducted and compared to ensure that GMO adopting countries share the common growing trend of agricultural LP and AP with non-GMO adopting countries before GMO varieties have been commercially planted.[11]

We next address the potential endogeneity problem. Labor choice, capital choice and GMO adoption may be affected by factors such as agricultural policies, attitudes towards GMOs and biotechnology and other macroeconomic variates not encompassed in our model. To remove such endogenous components, we use a two-stage least squares (2SLS) approach. Specifically, we construct an instrument for GMO adoption by using two sources of exogenous variation: cross-country variation in crop-specific pest shocks in the early 1990s and the differentiated timing of technology innovation across countries. The strategy used for constructing the instrument was initially developed by Nunn and Qian (2011), who use agro-climatic suitability to identify the impact of the potato on European development following the Colombian Exchange. More recently, Bustos et al. (2016) used a similar strategy to identify the effect of adopting genetically modified soybean and maize in Brazil, while Gollin et al. (2021) use agroclimatic suitability to estimate the impact of high-yielding varieties on economic growth in developing countries for the post-green revolution era. We use the crop-specific pest shocks across countries before 1990 to capture cross-country differences in potential gains from adopting GMO technologies. Because the cross-country differences in pest shocks are exogenously determined and most GMO varieties are designed to control

[11]The detailed results are reported in Annex B.

pests, they play an important role in identifying the timing and intensity of GMO adoption.

We construct our instrument for GMO adoption and intensity in two steps. The first uses the geographical variation of crop-specific pest shocks and the different timing of technology progress across countries to predict adoption intensity for each of the four major GMO crops j (namely, cotton, soybean, maize and canola) based on the following equation:

$$\begin{aligned} GMOS_{it}^{j} = &\sum_{k=1973}^{2016} \left(\alpha_k^j \cdot pestshk_i^j \cdot year_t^k\right) \\ &+ \sum_{k=1973}^{2016} \theta_k \cdot year_t^k + \sum_{c=2}^{N} \delta_c \cdot country_i^c + u_{it}^j \end{aligned} \tag{3}$$

where $GMOS_{it}^{j}$ is the GMO adoption intensity for crop j in country i at time period t and $pestshk_i^j$ is the occurrence of pests (sensitive to Bt toxin) for crop j across all land suitable for agriculture within a country before 1990. Because GMO varieties were bred and distributed across countries differently over time, we interact $pestshk_i^j$ with a full set of time-period fixed effects, $\sum_{k=1973}^{2016} \alpha_k^j * pestshk_i^j$. We also add year dummies, $year_t$, country fixed effects, $country_i$, to the regression. The residual is denoted by u_{it}^j.

In the second step, we multiply the predicted GMO adoption rates for each crop from equation (3), $G\hat{MOS}_{it}^{j}$, by its share in total cropping area in 1970. We then sum across crops to obtain the aggregate country-level predicted GMO adoption rate.

$$pGMOS_{it} = \sum_{j=1}^{J} \frac{G\hat{MOS}_{it}^{j} \cdot croppingarea_{i1970}^{j}}{\sum_{j=1}^{J} cropingarea_{1970}}, \tag{4}$$

The predicted GMO adoption rate, $pGMOS_{it}$, is our instrumental variable for the GMO adoption dummy and intensity. The relationship between the actual and the predicted GMO intensity for the year 2016 is shown in Figure B2. There is a strong positive correlation (i.e. 93.4%). The correlations in other time periods between 1994 and 2016 are similar.

As the instrument for capital intensity, we use the lagged relative price of capital formation compared to labor input at the national level. This is a valid instrument because agriculture is relatively a small sector among the OECD countries. In our sample, GDP share of agricultural sector in the overall economy is less than 3%. Thus, the choice of capital and labor input depends on the relative price of capital to labor for the economy.

We sourced these two measures from the Penn World Table 10.1, and used the price level of USA in 2005 as the baseline.[12] Finally, interaction between the two instrumental variables is used to identify the interaction between capital intensity and GMO adoption intensity.

With our instrumental variables in hand, we estimate the following first-stage equations:

$$G_{it} = \lambda_{01} + \lambda_{11} pGMOS_{it} + \lambda_{21} PAT_{it} + v_t + u_i + e_{it} \tag{5}$$

$$\ln k_{it} = \lambda_{02} + \lambda_{12} RP_{it} + v_t + u_i + e_{it} \tag{6}$$

$$G_{it} \ln k_{it} = \lambda_{03} + \lambda_{13} pGMOS_{it} \cdot RP_{it} + v_t + u_i + e_{it} \tag{7}$$

where $pGMOS_{it}$ is the predicted GMO adoption rate, which is the excluded instrument for actual GMO adoption rate in Equation (3). RP_{it} refers to the relative price of capital to labor. In order to improve identification, we add the accumulated number of GMO varieties and patents (PAT_{it}) in Equation (5). The remaining variables are defined as above. Predicted capital intensity, GMO adoption, and their interaction obtained from the first-stage regressions are used in the second-stage estimation.

Parameter estimates in 2SLS regressions with generated instruments are asymptotically distributed as in standard 2SLS regressions. The standard errors of the 2SLS estimate of α, b and β are thus asymptotically valid. In addition to the baseline 2SLS model represented by (3) and (4), we also conduct a set of robustness checks. In particular, we follow Gollin et al. (2021) to use the potential crop-specific yield gap between 1970-1990 and 1980-2000, determined by the cross-country difference in agro-climatic conditions, to approximate the potential difference in GMO adoption capacities across countries.

Our third step is to address the potential "negative" weight problem associated with applying the traditional TWFE model to multiple time-period shocks across countries. Recent studies show that the traditional TWFE model might not yield interpretable causal parameters, when external shocks are staggered (Sant'Anna and Zhao 2020; de Chaisemartin and D'Haultfoeuille 2020; Kirill Borusyak and Spiess 2021; Jonathan Roth and Poe 2022). In our case, GMO adoption occurs across countries at different time periods so that the average effect of GMO adoption may be contaminated as a result of the "negative" weight problem.

[12] Penn World Table 10.01 (https://www.rug.nl/ggdc/productivity/pwt/) with price level of USA (GDPo) in 2005 as the base.

We address this problem by following Sant'Anna and Zhao (2020), Callaway and Sant'Anna (2021), and Gardner (2021) to develop the difference-in-difference estimation procedure with multiple time periods. Specifically, take the estimate of α in Equation (2) as an example. We assume that l and k represent different cohorts for GMO adoption, the average impact of GMO adoption can be decomposed into:

$$\hat{\alpha} = \sum_{k \neq U} s_{kU}\hat{\alpha}_{kU} + \sum_{k \neq U}\sum_{l>k}[s_{kl}^{k}\hat{\alpha}_{kl}^{k} + s_{kl}^{l}\hat{\alpha}_{kl}^{l}]$$

where $\hat{\alpha}$ refers to average effect of GMO adoption to be estimated, l stands for early GMO adopting cohort and k stands for the late GMO adopting cohort, and

$$\begin{aligned}
\hat{\alpha}_{kU} &= (\overline{\ln y_k}^{POST(k)} - \overline{\ln y_k}^{PRE(k)}) - (\overline{\ln y_U}^{POST(k)} - \overline{\ln y_U}^{PRE(k)}) \\
\hat{\alpha}_{kl}^{k} &= (\overline{\ln y_k}^{MID(k,l)} - \overline{\ln y_k}^{PRE(k)}) - (\overline{\ln y_U}^{MID(k,l)} - \overline{\ln y_U}^{PRE(k)}) \\
\hat{\alpha}_{kl}^{l} &= (\overline{\ln y_k}^{POST(l)} - \overline{\ln y_k}^{MID(k,l)}) - (\overline{\ln y_U}^{POST(l)} - \overline{\ln y_U}^{MID(k,l)})
\end{aligned}$$

represent the AP effect from comparing early adopted with non-adopted countries, the AP effect from comparing late adopted with non-adopted countries, and the AP effect from comparing early and late adopting countries before l. Subscripts "PRE", "POST" and "MID" denote the stage of GMO adoption. The weights, $s_{(.)}$, are proportional to timing group sizes and the variance of the treatment dummy in each pair. When using a two-step procedure, we can also estimate β in a similar way.

We split our sample by different cohorts defined by l and k, and estimate effects of GMO adoption by using the TWFE model for each cohort dynamically. The estimated $\hat{\alpha}$'s and $\hat{\beta}$'s are then aggregated with corresponding weights for average effect of GMO adoption. We use two cross checks proposed by Callaway and Sant'Anna (2021) and Gardner (2021) respectively. Both the Bacon test proposed by Goodman-Bacon et al. (2019) and the negative weight test proposed by de Chaisemartin and D'Haultfoeuille (2020) have been conducted to examine the potential impact of the negative-weight problem on our estimation.[13] Additionally, we also use an approach developed by de Chaisemartin and D'Haultfoeuille (2020) to assess the impact of France and Germany revoking GMO approval in 2008 and 2012 respectively. We first estimate the average effect of GMO adoption by taking account of

[13]Please refer to the robustness check section for detailed estimation results.

the France and Germany's revocation of approval.[14] Then, we decompose average effects of GMO adoption into two components.[15]

Finally, the intensity with which GMOs are adopted across countries also varies. For example, the average GMO adoption intensity in the United States and Canada for the period of 1994-2016 are 45% and 23% respectively, while the adoption intensity for most EU adopters is less than 1%. Assigning equal weights to countries with different GMO adoption intensities in the regression analysis could bias the estimated impact of GMO adoption. We accommodate this problem by using the exponential of GMO adoption intensity (as regression weights) for each country to adjust the difference in GMO adoption intensity across countries.

Empirical Analysis

Table 1 presents summary sample statistics on agricultural LP, y, and capital intensity, k, segregated according to eventual adoption strategy. Figure 4 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 10% 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.

[14] In this exercise, the dummy of GMO adoption for France and Germany is assigned to be zero after 2008 and 2012 correspondingly.

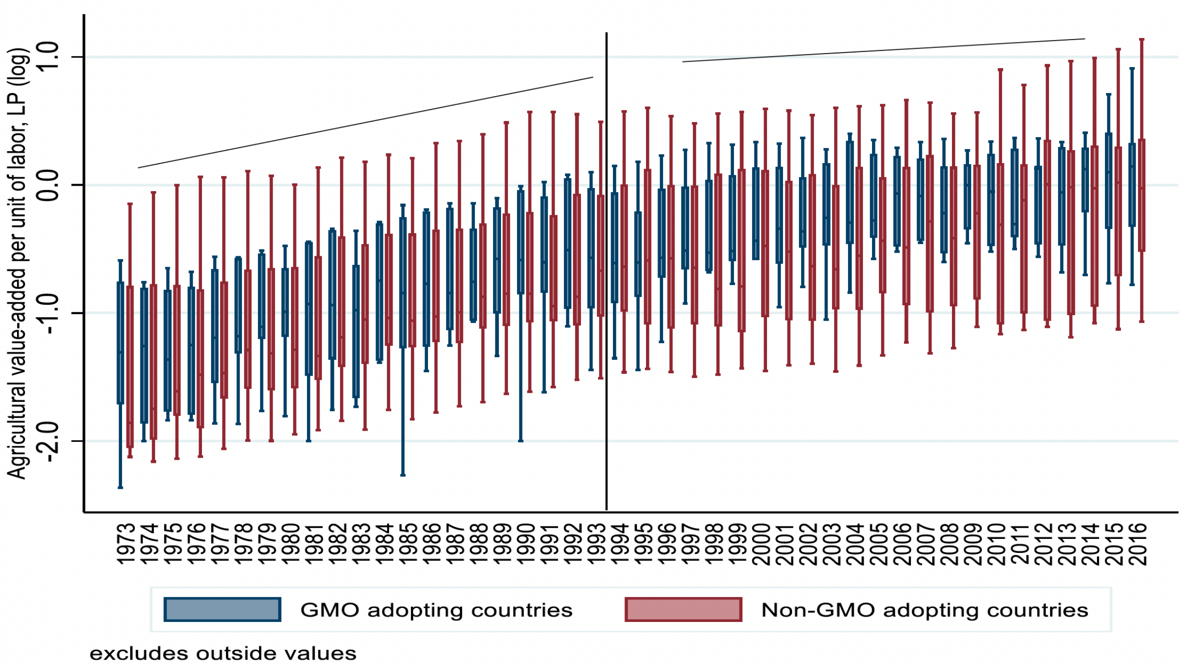
[15] In Annex B, we also conduct an exercise by treating France and Germany as non-GMO countries throughout the whole period and re-estimate the effect of GMO adoption as a robustness check.

Table 1: **Summary Statistics on labor productivity (y) and capital intensity (k) segregated by GMO adoption strategy**

	$\ln y$	$\ln k$	Num. of Obs.
non-GMO adopting countries	-0.665	-1.430	352
	(0.759)	(0.671)	
GMO adopting countries	-0.560	-1.296	308
	(0.594)	(0.626)	
pre-GMO adoption period (GMO countries)	-0.859	-1.473	179
	(0.535)	(0.612)	
post-GMO adoption period (GMO countries)	-0.146	-1.051	129
	(0.430)	(0.600)	

Note: $\ln y$ refers to the natural log of agricultural labor productivity, and $\ln k$ refers to the natural log of capital intensity. Standard deviations are reported in paratheses.

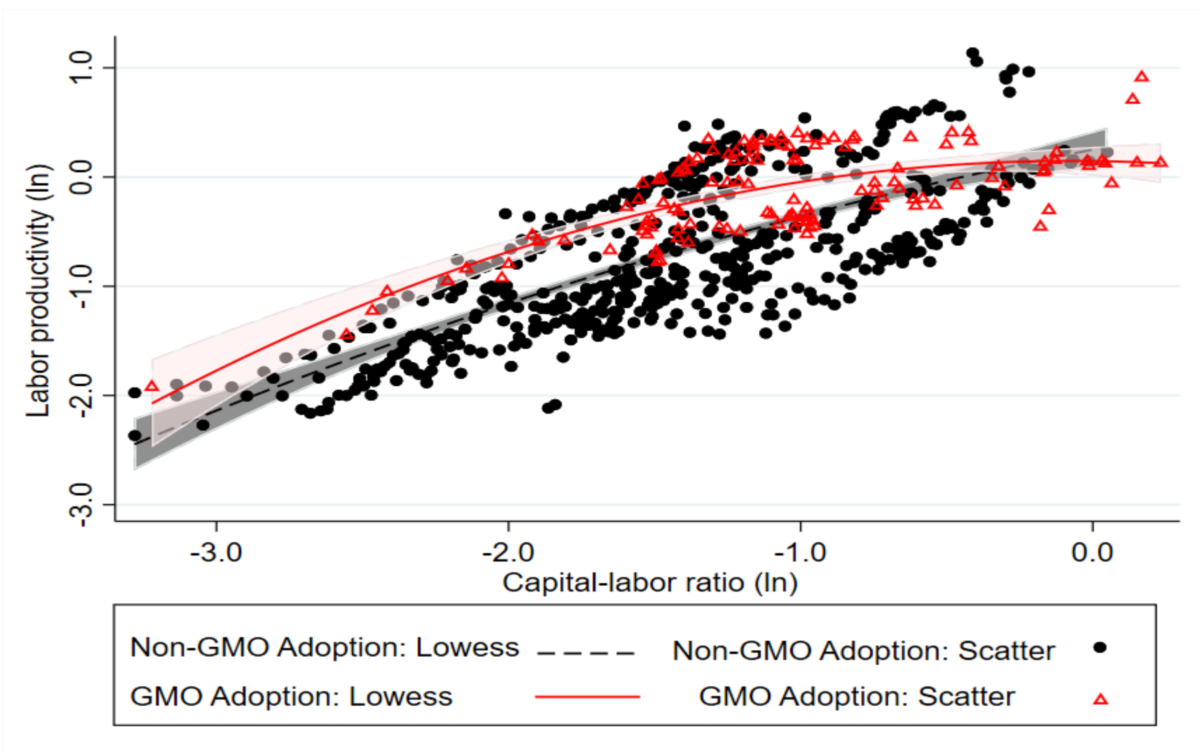
Figure 4: **Box plot of the natural log of agricultural labor productivity (y) segregated by GMO adoption strategy**



Note: Outliers are excluded for each year.

Figure 5 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 the highest levels of capital 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 5: **Scatter and LOWESS smoothed regression between agricultural labor productivity (y) and capital intensity (or capital-labor ratio, k) in natural log segregated by GMO adoption strategy**

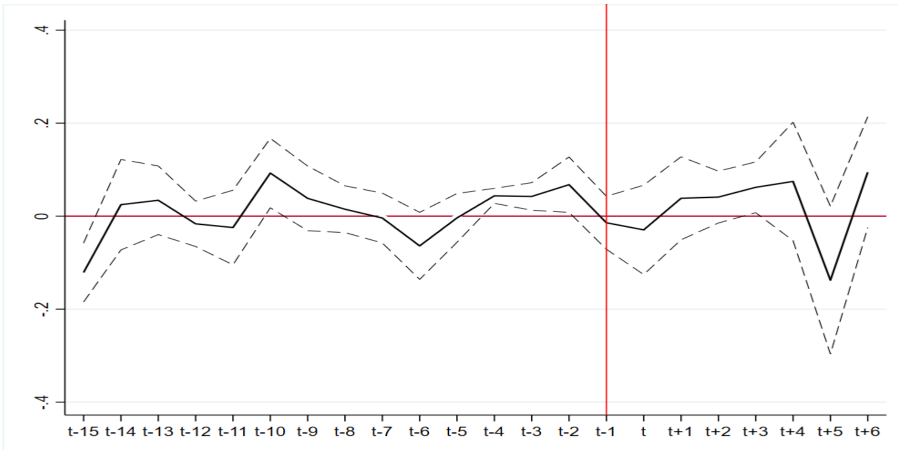


Note: The shades around the two fit lines represent the 95% confidence interval for LOWESS smooth regressions respectively.

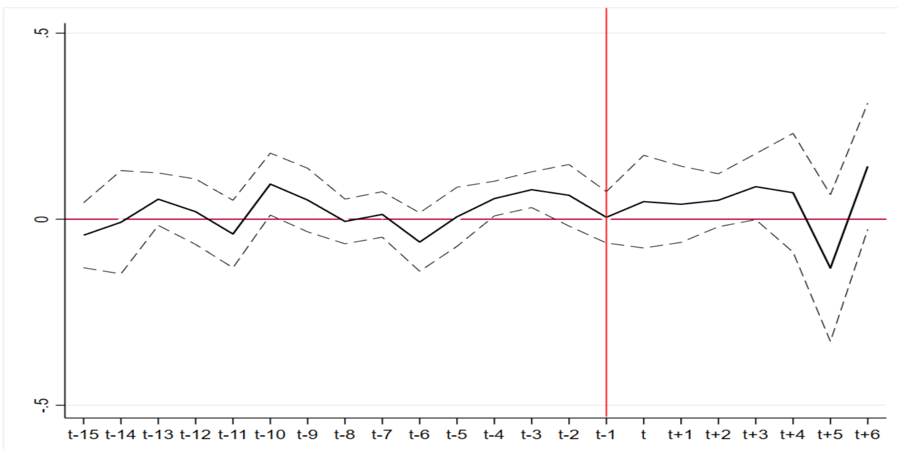
Using both the full sample and the PS-matched sample, we first conduct the parallel trend tests for agricultural LP based on 15 period lags and 6 period leads. The test results are presented in Figure 6. Based on the PS-matched sample, the F-statistic for the difference in agricultural LP growing trend between GMO and non-GMO countries over the pre-shock period jointly being equal to zero is 1.26 (p-value 39.22 %), which implies that the parallel trend test is passed at 5 % level. The comparable result for the full sample is 74.94 (p-value 0 %). The difference in the estimated F-statistics suggests that that the neighborhood matching approach alleviated the potential sample selection bias problem.[16]

[16] A more thorough parallel trend test with the consideration of the potential "negative weight" problem is also conducted and the results are shown in Figure 8, which also corroborates the finding that there is the parallel trend between GMO and non-GMO countries based on the PS-matched sample.

Figure 6: **Parallel Trend Test of agricultural labor productivity (y): Full sample vs. PS-matched sample**



(a) Full sample (95% confidence interval)



(b) PS-matched sample (95% confidence interval)

Note: the parallel trend tests are conducted for the natural log of agricultural labor productivity ($\ln y$) in a setting that contains 15 period lags and 6 periods leads.

Table 2 reports statistical estimates of b_0, α, and β obtained from the TWFE model using the OLS and 2SLS estimation method. 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 while ignoring the contribution of k. The estimated difference is positive but small, .17 log points, and imprecisely estimated.

Table 2: **Estimated impact of GMO adoption: 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					
1973-$\bar{v}$	-1.380***	0.183	0.177	-	-
	(0.079)	(0.167)	(0.274)	-	-
$\ln k_{it}$ (or b_0)	-	0.743***	0.708***	0.764***	0.764***
	-	(0.037)	(0.054)	(0.230)	(0.140)
G_{it} (or α)	0.174	-0.019	0.071	-0.091	-0.091
	(0.114)	(0.130)	(0.076)	(0.326)	(0.196)
$G_{it} * \ln k_{it}$ (or β)	-	-0.138*	-0.105**	-0.377**	-0.377**
	-	(0.077)	(0.050)	(0.165)	(0.099)
Number of Observations	660	660	403	403	403
R-squared	0.791	0.891	0.878	0.851	0.851
Number of countries	15	15	15	15	15

Note: Robust standard errors are reported in parentheses, and and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels. Other controls also include the Cluster Fixed Effects.

The second column reports OLS estimates of b_0, α, and β. The estimate for α becomes negative but remains imprecisely estimated. The OLS estimate for β is negative, about -.14 log points, and statistically significant at the 10% confidence level.

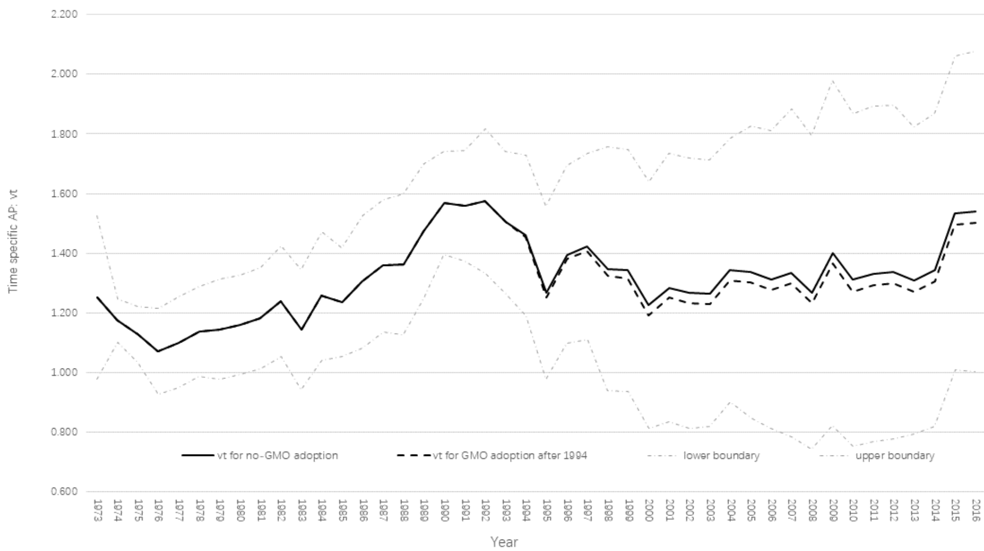
Column 3 repeats the regression analysis summarized in Column 2 using the common support sample (see Annex B for details) instead of the entire country panel. Column 4 reports parameters estimated using 2SLS in place of OLS applied to the common support sample, and Column 5 the 2SLS estimates obtained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

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 common support sample. Only the OLS estimate of α for the common support sample is positive. But it remains quite small, about .07 log points, and is imprecisely estimated. Both 2SLS estimates for α are negative, ranging from -0.02 to -.09. 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 three times larger (in absolute value terms) than the OLS estimates.

In Annex C, we report parameter estimates for $v_t - \bar{v}$, each period's deviation from the average AP for the non-GMO technology. Setting $v_{1973} = 1$ gives an estimate of approximately 1.42 for $\bar{v}$ using either version of the 2SLS estimates. Using this normalization, we calculated the v_t for the non-GMO technology using the 2SLS results from the matched but unweighted sample. Figure 7 portrays the results by the solid piece-wise linear curve. The pattern that emerges is a drop in period-specific AP during the First Oil Crisis of the early 1970s and then virtually uninterrupted growth until 1993.[17] In 1994 and 1995, the first two years of commercial GMO use, estimated v_t dropped approximately 10% and then leveled off, on average, for the balance of the sample period. The dotted piece-wise linear segment emanating from the solid curve depicts the impact, captured by our 2SLS estimate of α, of adopting GMO techniques in 1994 (the year in which they were introduced by the United States). The empirical results suggest that adopting GMO techniques in 1994 would have driven period-specific productivity below 1973 levels before 2012. The other dotted lines depict the associated confidence intervals at 95 % level.

[17] The perceptible dip in 1983-1984 reflects the US policy-driven PIK program that vastly curbed agricultural production.

Figure 7: Counterfactual analysis on GMO adoption impact: Agricultural Productivity (AP)



Note: the solid and dashed trend lines are drawn by using the estimated time-specific agricultural productivity (AP) effect (v_t) that represents time-varying productivity shocks (or technology progress) without and with the consideration of the impact of GMO adoption respectively. The lines in light colour provide the 95% confidence intervals.

While informative, the estimated α and β by using the traditional TWFE model is likely to be biased due to the potential "negative" weight problem discussed earlier. To assess the potential impact of "negative" weight, we performed the Goodman-Bacon (2020) test and the negative weight test proposed by de Chaisemartin and D'Haultfoeuille (2020). The results show that only 24% of the units in our regressions are ever treated, which implies that the problem is mitigated by the majority clean control.[18] Nevertheless, we still estimate α and β by using the approaches proposed by Callaway and Sant'Anna (2021) and Gardner(2021) and report the results in Table 3. Columns (1) and (2) of Table 3 provide the estimated α and β using the Callaway and Sant'Anna (2021) approach where non-adoption and not-yet adoption countries are used as control groups respectively, while columns (3) provides the estimated α

[18]See Annex B for the detailed Goodman-Bacon (2020) test results.

and β using the Gardner(2021) approach.[19] Throughout all model specifications, estimated α is negative ranging from -0.095 to -0.021 but imprecisely estimated, while estimated β is negative ranging from -0.199 to -0.110 and precisely estimated. These results support the findings of the OLS and 2SLS estimates.

Table 3: **Estimated impact of GMO adoption: CSDID (2020) and Gardner (2021)**

	CSDID (2021)	CSDID (2021)	Gardner (2021)
	Never	Not-yet	All
	(1)	(2)	(3)
Dependent variable: lny			
G_{it} (or α)	-0.029	-0.021	-0.096
	(0.060)	(0.067)	(0.126)
$G_{it} * lnk_{it}$ (or β)	-0.114**	-0.110*	-0.199**
	(0.070)	(0.061)	(0.078)
Number of Observations	357	412	403

Notes: In all regressions, we use IMP weights to aggregate the estimated treatment effects by cohort, and both country fixed effect and year effects have been accounted for. Other controls also include the Cluster Fixed Effects. Robust standard errors are reported in parentheses, and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels.

Finally, we estimate the impact of GMO adoption on agricultural labor productivity when taking into account of France and Germany's revocation of GMO approval. The estimated results obtained by using the de Chaisemartin and D'Haultfoeuille (2020) approach are reported in Table 4. Column (1) of Table 4 reports estimated average α and β when we consider the exit of Germany and France, while Column (2) and (3) decompose the average estimate into the roll-in and roll-out effects. On average, the estimated α is -0.635 and imprecisely estimated, while the estimated β is -0.171 and precisely estimated at 5%. When we only consider the impact of the first approval for GMOs by France and Germany in 1998 and 2000, the estimated α is -0.937 and imprecisely estimated at 10% level, while the estimated β is -0.159 and precisely estimated at 10%. The results imply that our findings

[19] In addition to estimate average effect, we have also conduct the eventual analyses to consider their dynamic changes and heterogeneous effects across cohorts. We report the corresponding dynamic estimates in the robustness check section.

Table 4: **Estimated impact of GMO adoption when considering Roll-out of France and Germany**

	Average	Roll-in effect	Roll-out effect
	(1)	(2)	(3)
Dependent variable: lny			
G_{it} (or α)	-0.635	-0.937	-0.091
	(0.773)	(1.000)	(0.409)
$G_{it} * lnk_{it}$ (or β)	-0.171**	-0.159*	-0.186*
	(0.097)	(0.114)	(0.094)
Number of Observations	451	451	451

Notes: We use the approach proposed by de Chaisemartin and D'Haultfoeuille (2020). In all regressions, both country fixed effects and year effects have been accounted for. Other controls also include the Cluster Fixed Effects. Robust standard errors are reported in parentheses, and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels.

of insignificant AP effect and significant negative effect on capital deepening are robust to accounting for French and German revocation.

As an alternative way to estimate the productivity effect of GMO adoption, we replicated the regression analyses using a direct measure of AP. Specifically, we constructed an aggregate of the K and L measures, denoted by X, and then measured AP by Y/X.[20] The newly constructed AP was used as the dependent variable and the resulting representation is

$$\ln(Y/X) = a(0) + \alpha G \tag{8}$$

The estimated results from (8) are summarized in Table 5.[21] The α estimate from OLS applied to the matched sample is positive and statistically different from zero at the 5% level. But, when we consider the potential endogeneity problem and the "negative weight" problem, the estimated results become unstable. Average 2SLS estimates for the matched

[20]The procedures for constructing the X aggregate follow those detailed in our Data section and in Annex A.

[21]The pretrend tests for the constructed AP are conducted by using both the full sample and the PS-matched sample, and the results are reported in Annex B. Based on the PS-matched sample, the pre-trend test has been passed which suggests that both GMO adoption and non-GMO adoption countries share the common trend before 1994.

sample is 0.091, while average estimates from the CSDID and Gardner (2021) analyses range from 0.043 to 0.133. All estimators are imprecisely estimated. For each of the estimated versions, the time-specific variates, $v_t - \bar{v}$ explained the bulk of the variation in AP. Thus, some support exists for the hypothesis that GMO adoption raises AP, but it disappears (and is reversed) when consistent estimation procedures are used.

Table 5: **Estimated impact of GMO adoption on agricultural productivity (AP, measured as value-added, Y, per unit of X): OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W	Never Treated	Notyet Treated	Gardner(2021)
	OLS	OLS	2SLS	2SLS	CSDID	CSDID	TSDID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: $lnAP$							
Constant	-1.402***	-1.299***	-	-	-	-	
	(0.082)	(0.131)	-	-	-	-	
G_{it} (or α)	0.136	0.215**	0.091	0.091	0.043	0.092	0.133
	(0.095)	(0.097)	(0.290)	(0.156)	(0.075)	(0.072)	(0.089)
Number of Observations	660	403	403	403	403	403	403
R-squared	0.717	0.709	0.701	0.701	-	-	-
Number of countries	15	15	15	15	15	15	15

Notes: In all regressions, both country fixed effects and year effects have been accounted for. The instrumental variable in use is same as that used for GMO adoption in Table 2. Other controls also include the Cluster Fixed Effects. Robust standard errors are reported in parentheses, and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels.

Robustness Checks

This section reports a series of robustness checks. The first check investigated the impact of GMO adoption when (2) and (8) were re-estimated after replacing the G_{it} variable by $GMOS_{it}$, where $GMOS_{it}$ is country i's GMO adoption intensity at time period t measured as actual planted area of GMO varieties divided by total cropping area of the country. The forms to be estimated are:

$$\ln y_{it} = c_0 + u_i + v_t + b_0 lnk_{it} + \alpha GMOS_{it} + \beta GMOS_{it} \ln k_{it} + \epsilon_{it}. \qquad (9)$$

and

$$\ln AP_{it} = c_0 + u_i + v_t + \alpha GMOS_{it} + \epsilon_{it}. \tag{10}$$

Table 6 summarizes the estimation results. These estimated coefficients have a different interpretation than those in Table 2. Nevertheless, the qualitative implications are similar. Higher intensities of GMO adoption are associated with lower or insignificant AP changes and a significantly lower marginal productivity of capital.[22]

Table 6: **Estimated impact of GMO adoption: GMO intensity (GMOS) replacing G (dummy for GMO)**

	$\ln y$	$\ln y$	$\ln AP$	$\ln AP$
	OLS+PSW	2SLS+PSW	OLS+PSW	2SLS+PSW
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln AP$				
1973-$\overline{v}$	0.178	-	-1.319***	-
	(0.234)	-	(0.136)	-
$\ln k$	0.716***	0.478***	-	-
	(0.120)	(0.152)	-	-
$GMOS$	-0.960	-2.118***	0.203	0.093
	(0.631)	(0.777)	(0.162)	(0.194)
$\ln k \cdot GMOS$	-1.078**	-1.989***	-	-
	(0.488)	(0.625)	-	-
Number of Observations	403	403	403	403
R-squared	0.873	0.858	0.687	0.686
Number of countries	15	15	15	15

Notes: In all regressions, both country fixed effects and year effects have been accounted for. Other controls also include the Cluster Fixed Effects. Robust standard errors are reported in parentheses, and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels.

Next we used the procedures developed by Autor (2003) and Beck et al. (2010) to examine the intertemporal behavior of GMO adoption and its impact on agricultural LP and AP. The

[22]In practice, there are lack of accurate statistics on the unreported (or illegal) plantation of GMO crops in GMO adopting countries. For example, many GMO adopting countries only treat GMO crop as its GMO varieties being more than 5 %. Thus, it is possible that using GMO intensity to approximate the adoption of GMO technology may underestimate its productivity effects.

corresponding empirical models are:

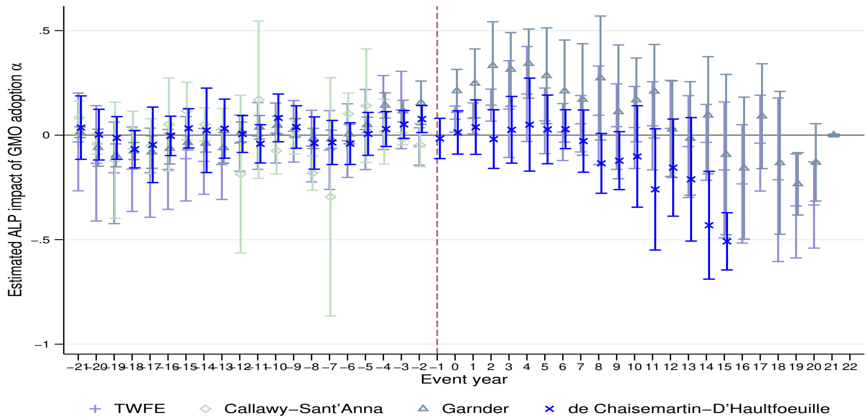
$$\ln y_{it} \;\; = \;\; c_0 + u_i + v_t + b_0 lnk_{it} + \sum_{j=-21}^{17} \alpha_j G_{it}^j + \sum_{j=-21}^{17} \beta_j G_{it}^j \ln k_{it}^j + \epsilon_{it}.$$

and

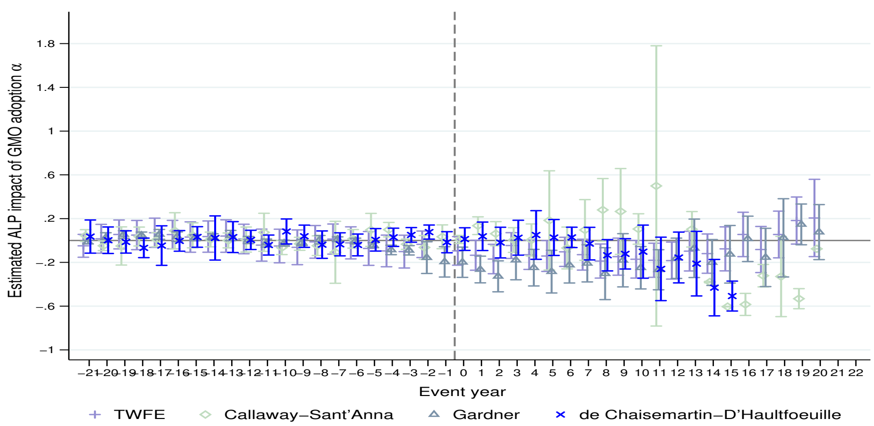
$$\ln AP_{it} \;\; = \;\; c_0 + u_i + v_t + \sum_{j=-21}^{17} \alpha_j G_{it}^j + \epsilon_{it}.$$

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. This dynamic analysis yields interpretable causal parameters that accommodate variation in treatment timing and heterogeneity of treatment effects (de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021). Given the recent challenges to TWFE designs in economics, we also examined average estimates of α and β aggregated by calendar years using the approach developed by Callaway and Sant'Anna (2021). The results are summarized and compared in panels (a)-(c) of Figure 8. For most years after GMO adoption, 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. The estimated coefficients, β_t, are consistently negative after 1994. The results are consistent and robust to various model specifications.

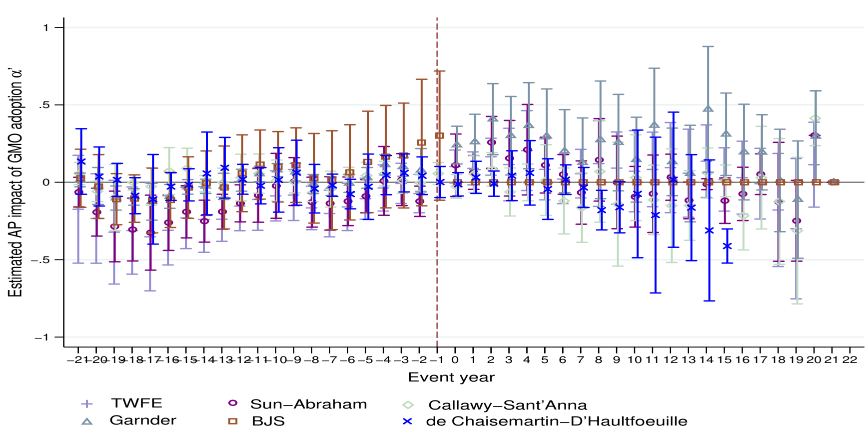
Figure 8: **Event analyses of the impact of GMO adoption on agricultural labor productivity (LP) and agricultural productivity (AP): Various Models**



(a) Estimated impact on agricultural labor productivity, LP (G)



(b) Estimated impact on agricultural labor productivity, LP ($G * \ln k$)



(c) Estimated impact on agricultural productivity, AP (G)

Note: To analyse the dynamic impact of GMO adoption on agricultural labor productivity (LP), we use four models including TWFE and another three other models following Callaway and Sant'Anna (2021), Gardner (2021) and de Chaisemartin and D'Haultfoeuille (2020). To analyse dynamic impact of GMO adoption on agricultural productivity (AP), we use six models including all the four models plus Sun and Abraham (2021) and BJS (2020).

Research and development (R&D) investment in agriculture, weather conditions, and crop share in agricultural output can affect agricultural productivity growth. Lusk et al. (2018) report that soil characteristics and weather conditions play important roles in GMO adoption decisions and determining their yield effects. Scheitrum et al. (2020) and Hansen and Wingender (2023b) found that GMO adoption would enhance the harvest areas of GMO crops. To examine the impacts of such productivity shifters, we incorporated three in our models (2) and (8).[23] These measured variates are public agricultural *R&D* knowledge stock constructed using data from Fuglie et al. (2022), the percentage of crop output in total agricultural output value, and the *Oury aridity index*.[24] The re-specified models are

$$\ln y_{it} = c_0 + u_i + v_t + b_0 lnk_{it} + \alpha G_{it} + \beta G_{it} \ln k_{it} + \gamma Z_{it} + \epsilon_{it}. \tag{11}$$

and

$$\ln AP_{it} = c_0 + u_i + v_t + \alpha G_{it} + \gamma Z_{it} + \epsilon_{it}. \tag{12}$$

where Z_{it} is a vector representing the three productivity shifters. Table 7 reports estimation results. The estimated impact of GMO adoption on AP, as measured by α, is positive but imprecise. Otherwise, our original results are qualitatively robust to these modeling changes.

In practice, average productivity impact of GMO adoption across countries comes from the aggregation of productivity impact of GMO adoption in each country. Given the limited number of countries in our sample, there is a concern that our finding of insignificant overall AP effect could result from the limited use of GMO technologies in the EU countries. To test this point, we use the regression control method (RCM) to examine the impact of GMO adoption on LP and AP in each GMO adopting country (Diamond et al. 2010; Craig et al.

[23]We thank Keith Fuglie for suggesting this analysis.

[24]The data on total precipitation and average temperature used to construct the Oury measures are from the World Bank Group's Climate Change Knowledge Portal.

Table 7: **Estimated impact of GMO adoption: With additional control variables**

	G	G	GMOS	GMOS
	$\ln y$	$\ln AP$	$\ln y$	$\ln AP$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln AP$				
G	-0.100	0.109	-	-
	(0.205)	(0.155)	-	-
$\ln k$	0.722***	-	-	-
	(0.152)	-	-	-
$G * \ln k$	-	-	-	
	(0.102)	-	-	-
$GMOS$	-	-	-2.159**	0.080
	-	-	(0.861)	(0.086)
$\ln k$	-	-	0.509**	-
	-	-	(0.204)	-
$GMOS * \ln k$	-	-	-2.087***	-
	-	-	(0.694)	-
R&D Stock	-0.090	0.104	-0.024	0.091
	(0.086)	(0.073)	(0.080)	(0.071)
Crop Value Share	0.614	-0.423	0.551	-0.379
	(0.445)	(0.303)	(0.419)	(0.343)
Oury Index	0.013	0.022	-0.003	0.015
	(0.070)	(0.063)	(0.061)	(0.065)
Number of Observations	403	403	403	403
R-squared	0.847	0.708	0.862	0.690
Number of countries	15	15	15	15

Note: The results reported in this table is obtained from Models (11) and (12), in which we control three additional variables. They include public knowledge stock (R&D Stock), the proportion of total value of cropping enterprises in total agriculture (Crop value share) and the Oury index for climatic conditions (defined as total rainfall dividing by average temperature). In all regressions, we use the 2SLS as the estimation method and both country fixed effects and year effects have been accounted for. Other controls also include the Cluster Fixed Effects. Robust standard errors are reported in parentheses, and "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels.

2018; Li et al. 2022). The essential idea of RCM is to use the combination of LP and AP for all the non-GMO adopting countries and their determinants to construct the counterfactual for the GMO adopting country through fitting the pre-treatment period, and then predict their post-treatment path had GMO technology not been adopted. Through comparing the predicted and the actual path, one can obtain average treatment effects of GMO adoption. Specifically, the baseline model can be written as:

$$\ln y_{1t} \quad = \quad \theta_0 + \theta_1 \ln y_t^{NG} + \epsilon_{1t}.$$

and

$$\ln AP_{1t} \quad = \quad \theta_0 + \theta_1 \ln AP_t^{NG} + \epsilon_{1t}.$$

where $\ln y_{1t}$ and $\ln AP_{it}$ refer to LP and AP of one GMO adoption country in year t, $\ln y_t^{NG}$ and $\ln AP_t^{NG}$ refer to LP and AP of non-GMO adoption countries and the covariantes from all GMO adoption countries in the pre-treatment period, such that ($\ln y_{2t}$,...,$\ln y_{nt}$, $\ln k_{1t}$,...,$\ln k_{nt}$, $Z_{1t}, ..., Z_{nt}$) and $(\ln AP_{2t}, ..., \ln AP_{nt}, Z_{1t}, ..., Z_{nt})$ and Z_{it} is a vector of control variables. Other variables are defined same as before. The estimation results are shown in Table 8. Among seven GMO adopting countries, three (including Canada, Germany and Spain) obtained more than 10% of positive AP effect and four (including Canada, Australia, Germany and Sweden) obtained more than 10% of positive LP effects (with the control of capital intensity). However, most of these positive LP and AP effects are observed in the EU countries where GMO planting intensities are relatively low. In contrast, average AP effect of GMO adoption is only 2.8 % in the US, where GMO intensity has reached 70 %, while average LP effect is negative. Our result suggests that a higher GMO adoption intensity (and a longer adoption period) does not necessarily induce a larger LP and AP effect. Additionally, GMO adoption has equal opportunity to affect LP and AP in EU countries as it does in non-EU countries. Meanwhile, the significant difference in LP and AP effects of GMO adoption also implies that capital deepening may play different roles in affecting LP across countries when GMO technology is adopted.

Finally, it might be argued that our results could be sensitive to different identification strategies. To resolve the problem, we perform the robustness check by using some alternative instrumental variables to identify GMO adoption. In particular, we use the change in potential yield gap across countries due to agroclimatic variation in geography between the

Table 8: **Estimated impact of GMO adoption on agricultural labor productivity (LP) and agricultural productivity (AP) by country: The regression control method (RCM)**

	ATE	CVMSE	Post/Pre MSPE ratio	ATE	CVMSE	Post/Pre MSPE ratio
	$\ln y$	$\ln y$	$\ln y$	$\ln AP$	$\ln AP$	$\ln AP$
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\ln y$ or $\ln AP$						
US	-0.122	0.013	0.588	0.028	0.014	0.824
CA	0.277	0.021	0.765	0.252	0.014	0.235
AU	0.282	0.006	0.471	-0.142	0.009	0.882
FR	-0.190	0.001	0.294	-0.264	0.001	0.059
DE	1.225	0.007	0.059	0.314	0.011	0.294
ES	0.048	0.015	0.765	0.204	0.036	0.882
SE	0.118	0.009	0.235	0.059	0.009	0.118
Number of donor pool countries	8	8	8	8	8	8

Notes: We use the regression control method to estimate the impact of GMO adoption on agricultural labor productivity (LP) and agricultural productivity (AP) for each country that has approved the commercial use of GMO technology. All the 8 non-GMO adoption countries are used as the donor pool, and they are also used for the placebo tests. The probability of obtaining a post/pre-treatment MSPS ratio is reported to inform the significance of the estimated productivity effects. In the first three columns (or LP model), we also control capital intensity.

1960-1980 period and the 1980-2000 period to approximate the cross-country difference in GMO adoption following Gollin et al. (2021). They are then interacted with the time fixed effects to pick up potential trend change in predicted agro-ecological condition based GMO adoption to generate the instrument for GMO adoption. The estimated results using the alternative instrumental variables corroborate the findings that we have obtained.[25]

Discussion: Existing Evidence and Our Findings

Our empirical results suggest that average GMO adopters experienced little to no statistically perceptible AP gains after adoption. The main impact of GMO adoption is to reduce the potential for capital deepening to enhance LP. The absence of a positive GMO impact on AP and the suggestion that introducing GMOs lowered AP may seem paradoxical, espe-

[25]The estimation results are available upon request from the authors.

cially given the existence of positive micro-level evidence. But 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 have revolutionized AP among developed countries, implying that the microeconomic literature (which shows a substantial positive productivity impact) could result from user-selection bias. Our empirical results also indicate that the period-specific component of AP slumped dramatically with the introduction of GMOs in the mid 1990s and largely failed to return to pre 1994 levels afterwards.

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 et al. (2018) concluded on the basis of an extensive time-series analysis that US agricultural multifactor productivity grew at an average annual rate of 1.16% over the 1990-2007 period as opposed to an average annual rate of 1.42% over the 1910-1990 period. The years 1994-2007 overlap the post-GMO-adoption period for the United States, and the Andersen et al. (2018) estimated .26 decline is consistent with our 2SLS estimates of a .09 decline, despite the differences in data and techniques.[26] Similarly, in a study focused on the effects of climate change Ortiz-Bobea et al. (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) compared the performance of adopters and non-adopters of GMO techniques.

Fernandez-Cornejo and McBride (2002) examined the economic impact of US GMO adoption prior to 2002. They found that the impact of GMO adoption varied substantially by crop and technical process. In particular, adopting herbicide-tolerant soybeans did not have a significant impact by 2002 even though adoption rates had reached 45% by then. The find-

[26]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.

ing is also confirmed by NASEM (2016), which also examined yield impact of GMO adoption on maize and cotton. Lusk et al. (2017) used a panel of US county-level data between 1980 and 2015 to examine the impact of GMO adoption on maize yield and found no yield trend change after GMO adoption. So did Hendricks et al. (2019). They both attributed the limited effect of GMO adoption in the US to changing weather patterns and different soil characteristics across locations. At a global level, Hansen and Wingender (2023a), applying a difference-in-difference strategy to four crops (including maize, soybean, cotton and canola) of 120 countries, found no effect of GMO adoption on maize and soybean yields in countries with climates and income similar to that of the US. Chambers and Sheng (2022) also used the same US state-level agricultural productivity data set as Ortiz-Bobea et al. (2018) with matching data on state-level GMO adoption rates to investigate the impact of GMO adoption on state-level agricultural productivity.[27] Their estimated α analogue to ours is positive but not statistically different from zero at all traditional confidence levels, even if state-level weather conditions and soil characteristics are properly controlled. They also report that the primary statistically-perceptible impact of GMO adoption is a lower marginal productivity of capital.[28]

The story that emerges is that the most perceptible difference between GMO adopters and non-adopters is in how capital deepening affects LP growth. Capital deepening is less effective in promoting LP growth among developed countries 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.[29] Six of the seven adopting

[27]The productivity accounts underlying the US state-level agricultural productivity data were constructed using different assumptions on aggregate agricultural technology than used in constructing our data. Where our data, following traditional productivity accounting methods impose constant returns to scale, the US state-level data do not.

[28]Because Chambers and Sheng (2022) do not impose constant returns in their analysis, the marginal productivity of capital and labor are captured by separate parameter estimates. For the specification, $Y = AK^bL^c$, their point estimates of b_0 and c_0 (for non adopters) are .525 (significantly different from zero at all traditional confidence levels) and .125 (not significantly different from zero at all traditional confidence levels), respectively.

[29]For all the countries in our panel, observed k is less than one. Therefore, under constant returns, a lower elasticity of output for K is associated with a higher LP.

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 2000-2016 period are (expressed in log points): United States (0.29), Canada (.47), Australia (-.08), France (.07), Spain (.14), and Germany (.33).[30] Sweden adopted GMO techniques in 2010 and our point estimate of that adoption's impact on LP for 2016 is -.15. So, according to these estimates, only Australia and Sweden experienced declines in both AP and LP, the rest experienced drops in AP but increases in LP.

Lacking further study, we can only speculate on the biological and mechanical forces driving these results, at least at the sector level. But existing work on the agricultural transformation offers some insights. For much of the last half of the 20th century, the stylized explanation for agricultural technical progress was the Hayami-Ruttan induced-innovation model (Hayami and Ruttan 1971). Technical progress is driven by market price signals reflecting relative factor scarcities. Thus, the land-abundant, labor-scarce United States developed land and capital intensive production techniques, while labor-rich countries such as Japan adopted labor-intensive techniques. Olmstead and Rhode (1993; 2008) have argued that historical factor price ratios moved in a direction counter to the Hayami-Ruttan hypothesis. And they conclude that settlement of Western lands, adapting crop patterns, and biological innovation better explain American agricultural development. Where Hayami and Ruttan (1971) and Olmstead and Rhode (1993; 2008) disagree on the role of induced innovation, they agree that location-specific factors play an important role in affecting productivity growth. Our finding that the main impact of GMO adoption on LP appears to be a weakening of the impact of capital deepening as a productivity driver is consonant with the Olmstead-Rhode hypothesis. We speculate that using GMO techniques may reduce the need for labor-intensive tasks such as weeding and pesticide application thus improving labor productivity.

Remarkably large agricultural LP differences exist between the richest and poorest coun-

[30] 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.

tries. For example, Tombe (2015) reports that agricultural LP in the 10 richest countries is 100 times that in the 10 poorest.[31] Restuccia et al. (2008) report a more conservative, but still large, factor of 78 between countries in the 90% and 10 % deciles. Because employment in poorer countries is much more concentrated in agriculture than in richer countries, reducing that agricultural productivity gap could be crucial to lifting their living standards to those of the poorer countries. Caselli (2005) calculations suggest, for example, that raising agricultural LP in the poorest countries to those in the United States would virtually eliminate world income inequality.

The empirical result that adopting GMO techniques can enhance LP for countries with labor-rich agricultural sectors suggests that GMO adoption might help eliminate the large labor productivity 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 two adopters. On average, Belgium, France, and the United States have roughly the same capital intensity (approximately, .26 to .30), while that in the Netherlands is considerably higher (.51). Average LP in France is approximately 93% of that in Belgium and 63% of that in the Netherlands.[32] The comparable US LP percentages are 84% and 79%. Moreover, when France adopted GMOs in 1998, its LP was approximately 77% of the Netherlands. In 2016, France's LP stood at 44% of the Netherlands. GMO adoption was accompanied by an increase and not a narrowing of the LP gap between France and the Netherlands. [33] Thus, while GMO adoption might enhance agricultural LP by increasing the marginal productivity of labor, our analysis suggests that more important drivers of LP are those captured by country-specific fixed effects.[34]

Finally, while many explanations, including farm size, transportation costs, and subsistence-driven labor selection effects and trade enhancing labor market distortions have been offered

[31]To be compared with a factor of 12 outside of agriculture.

[32]There is, however, considerable variability inter-annual variability.

[33]Such numbers, of course, are always subject to "cherry picking" and it is likely to be related with factors other than GMO adoption. For example, the Netherlands experienced a sharp drop in LP between 2010 and 2011 while France did not. If the same comparison were made for 2007 after which France revoked the use of Bt corn, France's LP was approximately 74% of the Netherlands.

[34]For example, it's important to understand that the United States has perhaps the most diverse agricultural sector, while other countries such as Belgium and Netherlands are much more specialized.

for the measured productivity gap (Adamopoulos and Restuccia 2014; Adamopoulos 2011; Lagakos and Waugh 2013; Tombe 2015), Restuccia et al. (2008) and Duncan et al. (2021) have suggested that existing market frictions retard the adoption of modern intermediate inputs. If true, the latter would suggest that similar frictions would inhibit effective adoption of GMO techniques that are often embodied in genetically altered seeds and other intermediate inputs.

Annex A. Production Accounts for Agriculture

The newly constructed production accounts for agriculture are designed for cross-country comparison of the relative levels of agricultural performance. It contains information used to measure outputs, inputs and total factor productivity of 15 OECD countries based on the valued model for the 1973-2016 period.

A.1 Output and intermediate input

Our measure of agricultural output includes deliveries to final demand and to intermediate demand in the nonfarm sector. We also include deliveries to intermediate farm demand so long as these deliveries are intended for different production activities (e.g., crop production intended for use in animal feeding).

An unconventional aspect of our measure of total output is the inclusion of output from "inseparable" secondary activities. These activities are defined as activities whose costs cannot be observed separately from those of the primary agricultural activity. Two types of secondary activities are distinguished. The first represents a continuation of the agricultural activity, such as the processing and packaging of agricultural products on the farm, while services relating to agricultural production, such as machine services for hire, are typical of the second.

The total output of the sector represents the sum of output of agricultural goods and the output of goods and services from secondary activities. We evaluate industry output from the point of view of the producer; that is, subsidies are added and indirect taxes are subtracted from market values.[1] In those countries where a forfeit system prevails, the difference between payments and refunds of the tax on value added (or VAT) is also included in the value of output.

Intermediate input consists of all goods and services consumed during the accounting

[1] Among the European countries, output is valued at basic prices. The "basic price" is the price received by the producer from the purchaser for a unit of a good or service produced as output minus any tax paid on that unit as a consequence of its production or sale (i.e., taxes on production) plus any subsidy received on that unit as a consequence of its production or sale (i.e., subsidies on products) (Eurostat, 2000, p. 43).

period, excluding fixed capital. Those goods and services that are produced and consumed within the agricultural sector are included in intermediate input so long as they also enter the farm output accounts. The value of intermediate input includes taxes (other than the deductible VAT) less subsidies, whether paid to suppliers of intermediate goods or to agricultural producers.[2]

We construct Tornqvist or translog price indices and implicit quantities of output and intermediate input for each of the 17 OECD countries over the period 1973 to 2016. To measure relative levels of output and intermediate input, we construct multilateral translog price indices for the year 2005 (see Caves, Christensen, and Diewert, 1982). These price indices are referred to in the literature as purchasing power parities (PPP). We extend these indices backward and forward in time using the intertemporal translog indices. This allows us to construct panel data that can be used for both cross-section and time series analysis.

A.2 Capital input

The measurement of capital input begins with data on the stock of capital and capital rental price for each asset type in each country.[3] At each point of time the stock of capital, say $K(T)$, is the sum of all past investments, say $I(T-\tau)$, weighted by the relative efficiencies of capital goods of each age τ, say $S(\tau)$.

$$K(T) = \sum_{\tau=0}^{\infty} S(\tau) I(T-\tau) \tag{A1}$$

To estimate capital stock, we must introduce an explicit description of the decline in efficiency. This function, S, may be expressed in terms of two parameters, the service life of the

[2]The data on output and intermediate input for the European countries are from the Economic Accounts for Agriculture NewCronos database http://epp.eurostat.ec.europe.eu/. Comparable data for the United States, Canada and Australia are available from the Economic Research Service, US Department of Agriculture, Statistics Canada, and the Australian Bureau of Statistics, respectively.

[3]Data on investment for the European countries are from Capital Stock Data for the European Union (Beutel, 1997). The series was extended through 2011 using Eurostat's NewCronos database http://europa.eu.int/comm/eurostat/newcronos/. Data for the United States are from Fixed Reproducible Tangible Wealth in the United States (U.S. Dept. of Commerce), and the data for Canada and Australia come from Statistics of Canada and Australian Bureau of Agricultural and Resource Economics and Sciences.

asset L and a curvature or decay parameter β. One possible form of the efficiency function is given by

$$\begin{aligned} S(\tau) &= (L-\tau)/(L-\beta\tau), \qquad (0 \leq \tau \leq L) \\ S(\tau) &= 0, \qquad\qquad\qquad\qquad\quad (\tau < L) \end{aligned} \tag{A2}$$

This function is a form of a rectangular hyperbola that provides a general model incorporating several types of depreciation as special cases.

The value of β is restricted only to values less than or equal to one. For values of β greater than zero, the function S approaches zero at an increasing rate. For values less than zero, S approaches zero at a decreasing rate.

Little empirical evidence is available to suggest a precise value for β. However, two studies (Penson et al. 1977; Romain et al. 1987) provide evidence that efficiency decay occurs more rapidly in the later years of service, corresponding to a value of β in the zero-one interval (Beutel, 1997; Baldwin et al. 2015). In this study, we assume that the efficiency of a structure declines very slowly over most of its service life. The decay parameter for machinery and transportation equipment assumes that the decline in efficiency is more uniformly distributed over the asset's service life. Given these assumptions, the final β values chosen were 0.75 for structures and 0.5 for machinery and equipment.

The other variable in the efficiency function is the asset life-time L. For each asset type, there exists some mean service life $\bar{L}$ around which there exists a distribution of actual service lives. In order to determine the amount of capital available for production, the actual service lives and the relative frequency of assets with these lives must be determined. It is assumed that this distribution may be accurately depicted by the normal distribution truncated at points two standard deviations before and after the mean service life.

Once the frequency of a true service life L is known, the decay function for that particular service life is calculated using the assumed value of β. This process is repeated for all other possible values of L. An aggregate efficiency function is then constructed as a weighted sum of individual efficiency functions using as weights the frequency of occurrence. This function not only reflects changes in efficiency, but also the discard distribution around the mean service life.[4]

[4] For further discussion, see Ball et al. (2008).

Firms undertaking investment decisions should add to capital stock if the present value of the net revenue generated by an additional unit of capital exceeds the purchase price of the asset. Stated algebraically, this condition is

$$\sum_{\tau=1}^{\infty}(P\frac{\partial Y}{\partial K} - W_K\frac{\partial R_t}{\partial K})(1+r)^{-t} > W_K \tag{A3}$$

where P is the price of output, W_K is the price paid for a new unit of capital, R_t is the replacement investment, and r is the real discount rate.

To maximize net worth, firms will add to capital stock until Equation (A3) holds as an equality

$$P = \frac{\partial Y}{\partial K} = rW_K + \sum_{\tau=1}^{\infty} W_K\frac{\partial R_t}{\partial K}(1+r)^{-t} = c \tag{A4}$$

where c is the implicit rental price of capital.

The rental price consists of two components. The first term, rW_K, represents the opportunity cost associated with the initial investment. The second term, $\sum_{\tau=1}^{\infty} W_K \frac{\partial R_t}{\partial K}(1+r)^{-t}$, is the present value of the cost of all future replacements required to maintain the productive capacity of the capital stock.

We can simplify the expression for the rental price in the following way. Let F denote the present value of the stream of capacity depreciation on one unit of capital according to the mortality distribution m

$$F = \sum_{\tau=1}^{\infty} m(\tau)(1+r)^{-t} \tag{A5}$$

where $m(\tau) = -[S(\tau) - S(\tau-1)], \quad (\tau = 1, 2, ..., L)$. It can be shown that

$$\sum_{\tau=1}^{\infty} W_K\frac{\partial R_t}{\partial K}(1+r)^{-t} = \frac{F}{1-F} \tag{A6}$$

so that

$$c = \frac{rW_K}{1-F} \tag{A7}$$

The real rate of return r in Equation (A7) is calculated as the nominal yield on government bonds less the rate of inflation as measured by the implicit deflator for gross domestic product.[35] An ex ante rate is obtained by expressing observed real rates as an ARIMA process.[36] We then calculate F holding the required real rate of return constant for that vintage of capital goods. In this way, implicit rental prices c are calculated for each asset type.

Although we estimate the decline in efficiency of capital goods for each component of capital input separately for all 17 countries, we assume that the relative efficiency of new capital goods is the same in each country. The appropriate purchasing power parity for new capital goods is the purchasing power parity for the corresponding component of investment goods output (OECD, 1999, p. 62). To obtain the purchasing power parity for capital input, we multiply the purchasing power parity for investment goods for any country by the ratio of the price of capital input in that country relative to the United States.

A.3 Land input

To estimate the stock of land in each country, we construct translog price indices of land in farms. The stock of land is then constructed implicitly as the ratio of the value of land in farms to the translog price index. The rental price is obtained using Equations (A7) assuming zero replacement.

Spatial differences in land characteristics or quality prevent the direct comparison of observed prices. To account for these differences, indexes of relative prices of land are constructed using hedonic regression methods in which a good is viewed as a bundle of characteristics that contribute to the productivity derived from its use. According to the hedonic framework the price of a good represents the valuation of the characteristics "that are bundled in it," and each characteristic is valued by its "implicit" price (Rosen, 1974). These prices are not observed directly and must be estimated from the hedonic price function.

A hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics it embodies. Thus, the hedonic price function for land may

[35] The nominal rate was taken to be the average annual yield over all maturities.

[36] Ex ante real rates are expressed as an AR(1) process. We use this specification after examining the correlation coefficients for autocorrelation, partial and inverse autocorrelation and performing the unit root and white noise tests. We centered each time series by subtracting its sample mean. The analysis was performed on the centered data.

be expressed as

$$W(\lambda) = \sum_n a_n X_n(\lambda_n) + \sum_d \gamma_d D_d + \epsilon \tag{A8}$$

where $W(\lambda)$ represents the price of land, X is a vector of characteristics, and D is a vector of other variables.

Sanchez et al. (2003) introduced a soil taxonomy that could be used to identify attributes relevant for crop production. A complete list of attributes, along with definitions, is provided in Sanchez et al. (2003). The attributes most common in major agricultural countries are loamy topsoil (particularly in the United States, Portugal and Spain) and moisture stress (particularly in Australia, Greece, Italy, Portugal and Spain). In areas with moisture stress, agriculture is not possible without irrigation. Hence, irrigation (i.e., the percentage of cropland that is irrigated) is included as a separate variable. We also include the interaction between moisture stress and irrigation in the hedonic regression.

In addition to environmental attributes, we also include a "population accessibility" score for each region in each country. This index is constructed using a gravity model of urban development, which provided a measure of accessibility to population concentrations (Shi et al., 1997). A gravity index accounts for both population density and distance from that population. The index increases as population increases and/or distance from the population center decreases.

Other variables (denoted by D) are also included in the hedonic equation, and their selection depends not only on the underlying theory but also on the objectives of the study. If the main objective of the study is to obtain price indexes adjusted for quality, as in our case, the only variables that should be included in D are country dummy variables, which will capture all price effects other than quality. After allowing for differences in the levels of the characteristics, the part of the price difference not accounted for by the included characteristics will be reflected in the country dummy coefficients.

Finally, economic theory places few if any restrictions on the functional form of the hedonic price function. In this study, we adopt a generalized linear form, where the dependent variable and each of the continuous independent variables is represented by the Box-Cox transformation. This is a mathematical expression that assumes a different functional form depending on the transformation parameter, and which can assume both linear and logarithmic forms, as well as intermediate nonlinear functional forms.

Ordinarily, estimating a Box-Cox model is straightforward. However, the fact that our model contains dichotomous variables with values equal to zero at some point(s) makes for a more difficult application of this procedure. Since the Box-Cox transformation involves logarithms, and the logarithm of zero is not defined, one cannot simply fit the Box-Cox model to the data. In response to this problem, we do not transform those quality variables with values of zero.

Several methods have been used to calculate price indexes adjusted for quality using hedonic functions, including characteristics prices and dummy variable techniques. The latter is used in this study because it is simpler and because Triplett (1989) has provided extensive evidence of the robustness of the hedonic price indexes to the method of calculation. Using the dummy variable approach, quality-adjusted price indexes are calculated directly from the coefficients on the country dummy variables D in the hedonic regression.

A.4 Labor input

Data on labor input in agriculture consist of hours worked disaggregated by hired and self-employed and unpaid family workers (Eurostat, 2000). 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 not directly observable. These data are derived using the accounting identify where the value of total product is equal to total factor outlay. Our index of labor input will then reflect differences in marginal products of hired and self-employed and unpaid family workers.

A.5 Other variables

We measure agricultural R&D by using the knowledge stock of public R&D investment in agriculture of the OECD countries estimated by Fuglie et al. (2022), based on the data of historical public expenditure in agricultural R&D. A gamma distribution with a time lag structure of 50 years are used to capture the time lag effects of agricultural R&D investment.

We measure climate condition by using the Oury (1965) index, which is defined as total precipitation dividing by $1.07^{temprature}$. Temperature is measured in degrees Celsius and precipitation in millimeters. The data on precipitation and temperature are sourced from the World Bank Group's Climate Change Knolwedge Portal. We measure agricultural output structure by using the value share of crop products in total output value. The data on each agricultural output of each commodity are sourced from agricultural production account that we have developed for the 15 OECD countries.

Annex B: Econometric Issues and Related Results

In this annex, we provide detailed discussion on how we resolve the four potential econometric issues mentioned in the main context.

First, it is to resolve the sample selection bias issue. 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*. 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.

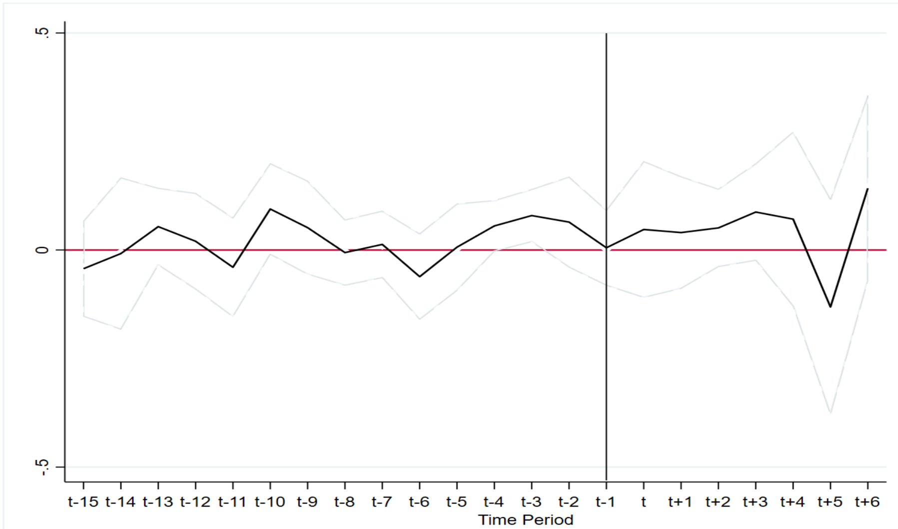
The estimated logit model is summarized in Annex Table B1. We use the estimated propensity scores to implement the one-to-one propensity score matching technique to match GMO approved and non-approved countries described, for example, in Imbens and Rubin (2015, see in particular Sections 15.3, 15.3.3,18.4-5). Briefly, in the pre-shock 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" (or common support sample) with 403 observations. Parallel trend tests for ALP and AP with 15 years of lag and 6 years in lead using both the "matched sample" are conducted, and the results are reported in Figure B1.

Table B1: **First-stage logit model for the propensity score (PS) matching**

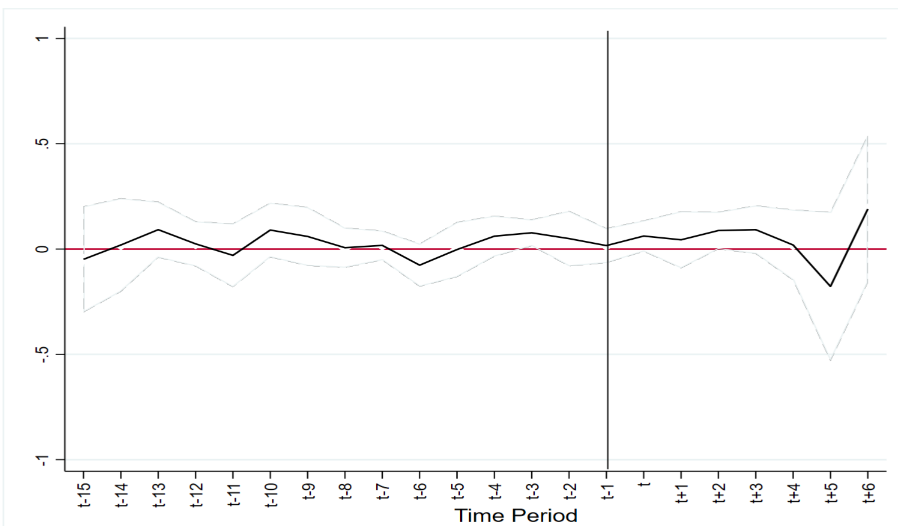
	Sub-sample (pre-1994)	All sample period
	(1)	(2)
Dependent variable: G_i		
GDP per capita (ln)	1.323**	0.375
	(0.567)	(0.408)
Relative price of intermediate inputs (US 1995=1)	-2.950***	-2.900***
	(0.573)	(0.391)
Constant	-11.597**	-2.252
	(5.704)	(4.092)
Year Dummies	Yes	Yes
Likelihood Ratio χ^2 (22/45)	47.45	67.33
Rseudo R-squared	0.109	0.074
Number of Observations	315	660

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

Figure B1: **The parallel trend test for GMO adoption using the propensity score matched sample: 95% level**



(a) Parallel trend test for ALP

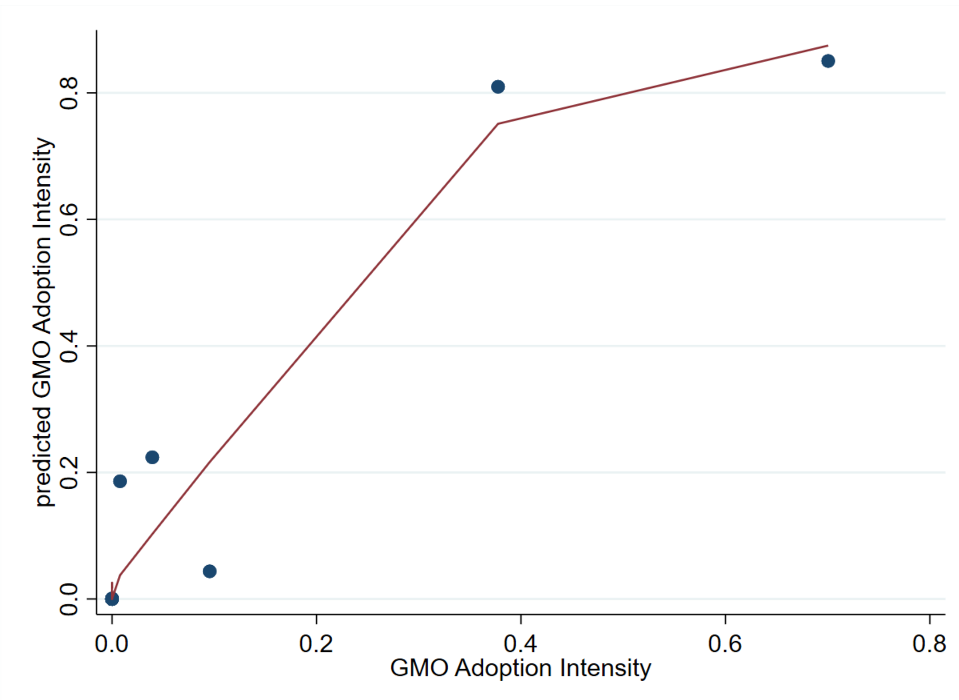


(b) Parallel trend test for AP

Note: we use 21 periods lags and 22 periods leads in this parallel trend test, and the F-statistics are 1.79 (p-value 24.81%) for ALP and 1.93 (p-value 22.16%) for AP compared to those obtained from using the full sample 1125.12 (p-value 0.00%) and 52.12(p-value 0.00%).

Second, it is about resolving the potential endogenous problem. Because labor choice, capital choice, and GMO adoption may be affected by factors such as agricultural policies, attitudes towards GMOs and biotechnology and macroeconomic shocks not encompassed in our model, we use a 2SLS procedure to accommodate the presence of missing explanatory factors. The instrument for GMO adoption and intensity in the first-stage regressions is the predicted GMO adoption rate. The instrument is generated by combining the cross-region variation of crop-specific pest shocks in the early 1990s with time variation arising from GMO adoption (for GMO adoption). The identification strategy has been previously used by Bustos and Ponticelli (2022) to identify the adoption of gene-modified corn and soybean in Brazil and by Gollin et al. (2021) to identify the adoption of high-yielding varieties in the green revolution era. Figure B2 shows the scatter plot between actual GMO adoption and predicted GMO adoption in the year 2016 (corresponding to the change between 1994 and 2016 as GMO adoption is zero for all countries before 1994). There is a strong positive correlation between actual GMO adoption and predicted GMO adoption rates.

Figure B2: Actual and predicted GMO adoption (in the year 2016)



For capital intensity, we use the lagged relative price of capital formation at the national level (for capital intensity) as the instrument, and the interaction between the two instrumental variables for the interaction term between GMO adoption and capital intensity. All three regressions were estimated in the panel data regression with the control of country fixed effects. The first-stage results are summarized in Table B2.

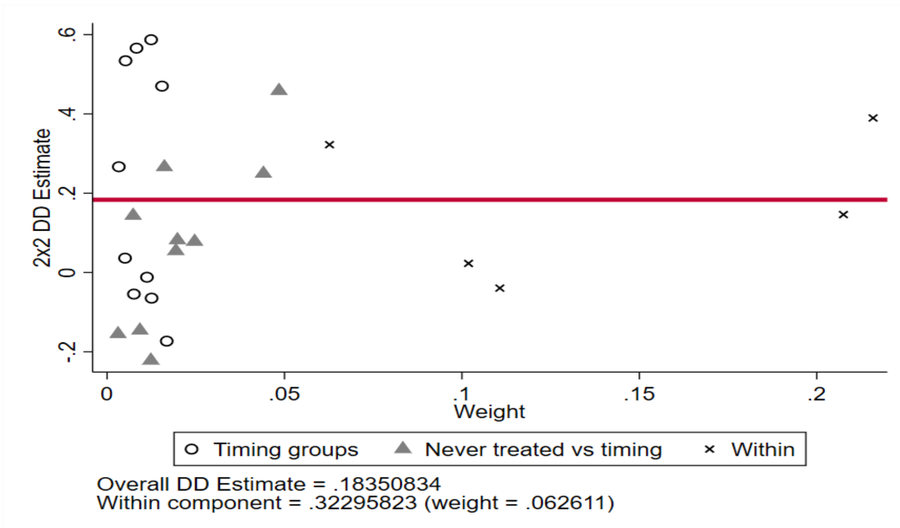
Table B2: **The first-stage regression results for the 2SLS models**

	Model (4) and (5)		
	(1)	(2)	(3)
Dependent variable:	lnk_{it}	G_{it}	$G_{it} * lnk_{it}$
Relative price of capital to labor	0.554***	-0.462***	1.283***
	(0.132)	(0.147)	(0.215)
predicted GMO adoption rate	0.050	-1.429***	-0.241
	(0.257)	(0.328)	(0.487)
Number of patents applicants (10 years ahead)	-	0.000	0.000
	-	(0.000)	(0.000)
Number of GMO events (10 years ahead)	-	0.003**	-0.011***
	-	(0.001)	(0.003)
Interactions between capital price and predicted GMO adoption rate (10 years ahead)	-0.197	0.897***	-1.134***
	(0.263)	(0.217)	(0.389)
Country-specific effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
F-test of excluded instruments	29.02	23.55	69.56
Sanderson-Windmeijer multivariate F test	33.84	10.90	14.73
Kleibergen-Paap rk LM stat.	23.076		
Weak identification test		9.793	
Hansen J statistic (over-identification test		7.286	

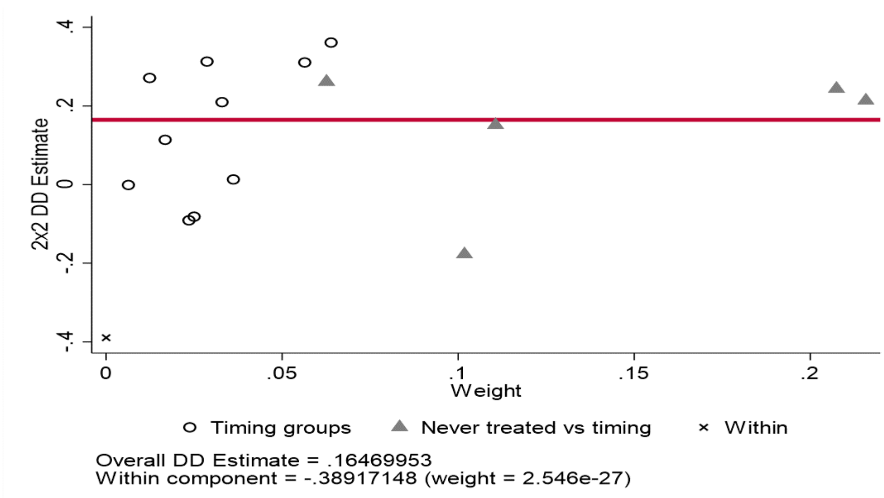
Notes: Robust standard errors in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Third, it is to cope with the "negative weight" problem in the traditional TWFE model. Estimators based on the staggered shocks are sometimes difficult to interpret because of a potential "negative" weight problem. This could cause causing the traditional TWFE model not to yield interpretable α and β in our framework. To resolve this problem, we conducted the Goodman-Bacon (2018) test to examine how the important the potential "negative" weight problem is in our study. As is shown in Figure B3, the test results show that: for the ALP regression, there are totally 129 ATTs under the common trends assumption, among which 98 ATTs receive a positive weight and 31 ATTs receive a negative weight. In other words, only 24% of the units in our regressions received negative weights, so the problem is mitigated by the many clean controls. Moreover, we also conducted the test proposed by de Chaisemartin and D'Haultfoeuille (2020) and the test result shows that the null hypothesis that the estimated impact is comparable with a DGP is not rejected at 5%. Nevertheless, we also follow Sant'Anna and Zhao (2020), Callaway and Sant'Anna (2021) and Gardner (2021) to provide alternative estimates of average α and β and their aggregation by groups and calendar years. A similar result also applies to the AP regression.

Figure B3: Goodman-Bacan Test for "negative weight": LP and AP



(a) Test for LP



(b) Test for AP

While France and Germany approve the adoption of GMO in 1998 and 2000, they are not important GMO adopters compared to other EU countries (i.e. Spain and Sweden). Both countries, in effect, banned the use of GMOs in 2008 and 2012 respectively, and as a consequence, GMO crops never represented a significant amount of acreage in these countries. To address this problem, we use the approach proposed by de Chaise-martin and D'Haultfoeuille

(2020) to assess the impact of France and Germany revoking GMO approval. Additionally, we also conduct an alternative analysis that treated France and Germany as non-GMO countries throughout the whole period. The results are reported in Annex Table B3. Generally, our findings of negative and insignificant impact of GMO adoption on AP and significant negative impact of GMO adoption on capital deepening still hold when both France and Germany are treated as non-GMO countries.

Table B3: **Estimation Results from the Model Treating France and Germany as Non-GMO Countries**

	G		GMOS	
	$\ln y$	$\ln Y/X$	$\ln y$	$\ln Y/X$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln Y/X$				
G_{it} (or α)	0.031	0.020	-	-
	(0.103)	(0.108)	-	-
$\ln k_{it}$ or (b_0)	0.532***	-	-	-
	(0.094)	-	-	-
$G_{it} * \ln k_{it}$ or (β)	-0.202***	-	-	-
	(0.059)	-	-	-
$GMOS$	-	-	-2.822***	-0.233**
	-	-	(1.087)	(0.096)
$\ln k$	-	-	0.416**	-
	-	-	(0.197)	-
$\ln k * GMOS$	-	-	-2.297***	-
	-	-	(0.831)	-
Number of Observations	403	403	403	403
R-squared	0.873	0.695	0.858	0.692
Number of countries	15	15	15	15

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

Finally, we also use GMO intensity as the independent variable (replacing the dummy for GMO adoption) and re-do the exercise as in the robustness check. This analysis is similar as a generalized difference-in-difference procedure, which not only accounts for the potential exit of some countries but also accounts for the intensity of GMO adoption intensity and its impact on agricultural LP and AP.

In Table B4, we also report the estimation results using alternative IVs.

Table B4: **Estimation Results using Alternative Instrumental Variables: Potential Yield Gap**

	G		GMOS	
	$\ln y$	$\ln Y/X$	$\ln y$	$\ln Y/X$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln Y/X$				
G_{it} (or α)	-0.085	0.090	-	-
	(0.188)	(0.156)	-	-
$\ln k_{it}$ (or b_0)	0.763***	-	-	-
	(0.140)	-	-	-
$G_{it} * \ln k_{it}$ (or β)	-0.374***	-	-	-
	(0.095)	-	-	-
$GMOS$	-	-	-2.120***	0.095
	-	-	(0.778)	(0.193)
$\ln k$	-	-	0.480***	-
	-	-	(0.153)	-
$\ln k * GMOS$	-	-	-1.992***	-
	-	-	(0.625)	-
Number of Observations	403	403	403	403
R-squared	0.851	0.700	0.858	0.686
Number of countries	15	15	15	15

Notes: The instrumental variables used in this table is the potential yield gap estimated by using FAO GERD data. Robust standard errors are in parentheses, and "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Annex C: Time-specific AP Change and Its Impact

In this section, we report the full set of estimates for those summarized in Table 2 (Annex Table C1), Table 5 (Annex Table C2) and Table 6 (Annex Table C3) in the main context.

Table C1: **Complete estimation results LP dependent variable: 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					
$\ln k_{it}$ (or b_0)	0.174	-0.019	0.071	-0.091	-0.091
	(0.114)	(0.130)	(0.076)	(0.326)	(0.196)
$G_{it} * \ln k_{it}$ (or α)	0.743***	0.708***	0.764***	0.764***	
	(0.087)	(0.051)	(0.230)	(0.140)	
$G_{it} * \ln k_{it}$ (or β)	-0.138*	-0.105**	-0.377**	-0.377***	
	(0.077)	(0.050)	(0.165)	(0.099)	
year==1974	0.027	-0.036	-0.052	-0.062	-0.062
	(0.038)	(0.023)	(0.121)	(0.073)	(0.130)
year==1975	0.085	-0.025	-0.087	-0.103	-0.103
	(0.055)	(0.039)	(0.120)	(0.094)	(0.134)
year==1976	0.087	-0.059	-0.124	-0.154	-0.154
	(0.071)	(0.060)	(0.113)	(0.143)	(0.130)
year==1977	0.169**	-0.036	-0.095	-0.128	-0.128
	(0.068)	(0.057)	(0.112)	(0.152)	(0.132)
year==1978	0.254***	-0.001	-0.062	-0.095	-0.094
	(0.075)	(0.058)	(0.112)	(0.151)	(0.134)
year==1979	0.287***	-0.008	-0.049	-0.089	-0.088
	(0.078)	(0.060)	(0.106)	(0.168)	(0.134)
year==1980	0.309***	-0.017	-0.036	-0.074	-0.074
	(0.086)	(0.068)	(0.115)	(0.166)	(0.140)
year==1981	0.315***	0.010	-0.023	-0.057	-0.057
	(0.069)	(0.065)	(0.108)	(0.169)	(0.129)
year==1982	0.420***	0.071	0.028	-0.010	-0.010
	(0.078)	(0.071)	(0.109)	(0.186)	(0.135)
year==1983	0.374***	0.003	-0.045	-0.089	-0.089
	(0.101)	(0.077)	(0.116)	(0.202)	(0.143)
year==1984	0.518***	0.111	0.051	0.005	0.005
	(0.096)	(0.080)	(0.108)	(0.214)	(0.140)
year==1985	0.464***	0.091	0.018	-0.012	-0.012
	(0.093)	(0.080)	(0.113)	(0.182)	(0.133)
year==1986	0.555***	0.129	0.084	0.042	0.042
	(0.096)	(0.076)	(0.107)	(0.223)	(0.142)
year==1987	0.606***	0.138*	0.121	0.082	0.082
	(0.092)	(0.074)	(0.107)	(0.222)	(0.145)
year==1988	0.668***	0.165**	0.133	0.085	0.085
	(0.105)	(0.070)	(0.106)	(0.236)	(0.151)
year==1989	0.698***	0.222***	0.201*	0.164	0.165
	(0.091)	(0.071)	(0.105)	(0.225)	(0.142)
year==1990	0.709***	0.250***	0.254**	0.226	0.226*
	(0.080)	(0.068)	(0.105)	(0.173)	(0.132)
year==1991	0.728***	0.231***	0.253**	0.220	0.220
	(0.063)	(0.064)	(0.107)	(0.187)	(0.144)
year==1992	0.812***	0.270***	0.281**	0.231	0.231
	(0.064)	(0.073)	(0.111)	(0.243)	(0.161)

Table C1 continued: **Complete estimation results LP dependent variable: 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					
year==1993	0.821***	0.266***	0.231**	0.184	0.185
	(0.081)	(0.077)	(0.112)	(0.238)	(0.158)
year==1994	0.839***	0.268***	0.230**	0.155	0.155
	(0.093)	(0.075)	(0.109)	(0.269)	(0.168)
year==1995	0.816***	0.242***	0.159	0.014	0.014
	(0.110)	(0.081)	(0.114)	(0.289)	(0.210)
year==1996	0.847***	0.279***	0.236**	0.110	0.111
	(0.093)	(0.081)	(0.111)	(0.297)	(0.195)
year==1997	0.872***	0.285***	0.259**	0.130	0.130
	(0.086)	(0.082)	(0.115)	(0.313)	(0.201)
year==1998	0.874***	0.282***	0.258**	0.076	0.076
	(0.087)	(0.076)	(0.116)	(0.409)	(0.228)
year==1999	0.893***	0.289***	0.244*	0.072	0.073
	(0.093)	(0.079)	(0.125)	(0.404)	(0.231)
year==2000	0.866***	0.270**	0.194	-0.019	-0.019
	(0.122)	(0.092)	(0.121)	(0.412)	(0.241)
year==2001	0.916***	0.277***	0.220*	0.028	0.029
	(0.104)	(0.083)	(0.115)	(0.450)	(0.242)
year==2002	0.919***	0.269**	0.196*	0.014	0.014
	(0.107)	(0.092)	(0.119)	(0.452)	(0.239)
year==2003	0.904***	0.261**	0.195	0.013	0.013
	(0.101)	(0.092)	(0.122)	(0.447)	(0.237)
year==2004	0.988***	0.310***	0.239**	0.073	0.074
	(0.104)	(0.098)	(0.121)	(0.440)	(0.237)
year==2005	1.041***	0.307***	0.228*	0.068	0.068
	(0.124)	(0.101)	(0.128)	(0.489)	(0.254)
year==2006	1.038***	0.278***	0.198*	0.049	0.050
	(0.122)	(0.093)	(0.118)	(0.497)	(0.255)
year==2007	1.067***	0.270**	0.226*	0.066	0.067
	(0.135)	(0.092)	(0.126)	(0.549)	(0.276)
year==2008	1.016***	0.232**	0.185	0.016	0.016
	(0.120)	(0.105)	(0.128)	(0.525)	(0.267)
year==2009	1.122***	0.277**	0.264*	0.115	0.116
	(0.136)	(0.097)	(0.139)	(0.577)	(0.286)
year==2010	1.065***	0.233**	0.179	0.049	0.050
	(0.135)	(0.097)	(0.131)	(0.557)	(0.285)

Table C1 continued: **Complete estimation results LP dependent variable: 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					
year==2011	1.100***	0.255**	0.200	0.065	0.066
	(0.138)	(0.105)	(0.129)	(0.561)	(0.293)
year==2012	1.154***	0.295***	0.190	0.070	0.070
	(0.140)	(0.086)	(0.126)	(0.559)	(0.295)
year==2013	1.135***	0.257**	0.162	0.048	0.048
	(0.135)	(0.099)	(0.129)	(0.515)	(0.282)
year==2014	1.193***	0.318***	0.169	0.074	0.075
	(0.131)	(0.100)	(0.128)	(0.524)	(0.288)
year==2015	1.242***	0.402***	0.310**	0.207	0.207
	(0.142)	(0.118)	(0.141)	(0.526)	(0.283)
year==2016	1.294***	0.425***	0.313**	0.210	0.211
	(0.145)	(0.130)	(0.146)	(0.538)	(0.294)
Constant	-1.380***	0.185	-	-	
	(0.079)	(0.167)	-	-	
Observations	660	660	403	403	403
R-squared	0.791	0.891	0.878	0.851	0.851
Number of regcode	15	15	15	15	15
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

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

Table C2: **Complete estimation results AP dependent variable: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: : $lnAP$				
G_{it} (or α)	0.136	0.215**	0.091	0.091
	(0.095)	(0.097)	(0.290)	(0.156)
year==1974	0.025	-0.005	0.001	0.001
	(0.034)	(0.064)	(0.066)	(0.158)
year==1975	0.059	-0.056	-0.046	-0.046
	(0.052)	(0.091)	(0.093)	(0.156)
year==1976	0.040	-0.061	-0.043	-0.043
	(0.073)	(0.109)	(0.123)	(0.149)
year==1977	0.094	0.025	0.040	0.040
	(0.073)	(0.108)	(0.120)	(0.139)
year==1978	0.150*	0.077	0.089	0.089
	(0.085)	(0.122)	(0.130)	(0.137)
year==1979	0.182**	0.135	0.150	0.150
	(0.081)	(0.118)	(0.135)	(0.134)
year==1980	0.207**	0.178	0.188	0.188
	(0.086)	(0.128)	(0.137)	(0.141)
year==1981	0.237***	0.187	0.197*	0.197
	(0.075)	(0.108)	(0.115)	(0.138)
year==1982	0.321***	0.257**	0.267**	0.267**
	(0.081)	(0.116)	(0.122)	(0.136)
year==1983	0.251**	0.179	0.195	0.195
	(0.097)	(0.129)	(0.140)	(0.149)
year==1984	0.382***	0.278*	0.293**	0.293**
	(0.088)	(0.130)	(0.143)	(0.134)
year==1985	0.376***	0.287**	0.293**	0.293**
	(0.089)	(0.133)	(0.131)	(0.134)
year==1986	0.429***	0.351**	0.363**	0.363***
	(0.093)	(0.137)	(0.146)	(0.129)
year==1987	0.461***	0.400**	0.406***	0.406***
	(0.087)	(0.143)	(0.140)	(0.128)
year==1988	0.505***	0.419**	0.432***	0.432***
	(0.092)	(0.144)	(0.155)	(0.129)
year==1989	0.558***	0.482***	0.488***	0.488***
	(0.090)	(0.145)	(0.142)	(0.128)
year==1990	0.591***	0.544***	0.544***	0.544***
	(0.080)	(0.118)	(0.108)	(0.132)
year==1991	0.572***	0.556***	0.556***	0.556***
	(0.072)	(0.111)	(0.101)	(0.130)

Table C2 continued: **Complete estimation results AP dependent variable: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: $lnAP$				
year==1992	0.621***	0.582***	0.592***	0.592***
	(0.070)	(0.121)	(0.127)	(0.131)
year==1993	0.629***	0.544***	0.554***	0.554***
	(0.083)	(0.131)	(0.137)	(0.132)
year==1994	0.635***	0.528***	0.549***	0.549***
	(0.092)	(0.139)	(0.162)	(0.133)
year==1995	0.622***	0.457***	0.512**	0.512***
	(0.098)	(0.137)	(0.234)	(0.153)
year==1996	0.659***	0.556***	0.606***	0.606***
	(0.092)	(0.132)	(0.224)	(0.146)
year==1997	0.666***	0.576***	0.629***	0.629***
	(0.090)	(0.144)	(0.243)	(0.151)
year==1998	0.662***	0.578***	0.659**	0.660***
	(0.083)	(0.137)	(0.306)	(0.174)
year==1999	0.678***	0.562***	0.644**	0.645***
	(0.088)	(0.154)	(0.323)	(0.183)
year==2000	0.679***	0.532***	0.629*	0.629***
	(0.100)	(0.144)	(0.334)	(0.187)
year==2001	0.685***	0.552***	0.651*	0.651***
	(0.099)	(0.143)	(0.342)	(0.187)
year==2002	0.681***	0.514***	0.610*	0.610***
	(0.102)	(0.162)	(0.350)	(0.190)
year==2003	0.672***	0.524***	0.617*	0.618***
	(0.101)	(0.173)	(0.350)	(0.191)
year==2004	0.734***	0.590***	0.679**	0.679***
	(0.102)	(0.167)	(0.333)	(0.183)
year==2005	0.747***	0.564***	0.661*	0.661***
	(0.112)	(0.184)	(0.369)	(0.198)
year==2006	0.725***	0.553***	0.648*	0.648***
	(0.110)	(0.171)	(0.351)	(0.189)
year==2007	0.736***	0.605***	0.709*	0.709***
	(0.121)	(0.188)	(0.374)	(0.204)
year==2008	0.692***	0.535***	0.637*	0.637***
	(0.116)	(0.178)	(0.361)	(0.196)

Table C2 continued: **Complete estimation results AP dependent variable: OLS and 2SLS**

	All Sample	PS Match	PS Match	PS Match+W
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Dependent variable: $lnAP$				
year==2009	0.748***	0.625***	0.731*	0.731***
	(0.121)	(0.197)	(0.381)	(0.210)
year==2010	0.692***	0.567**	0.676*	0.676***
	(0.127)	(0.195)	(0.387)	(0.209)
year==2011	0.733***	0.565***	0.689*	0.689***
	(0.128)	(0.162)	(0.403)	(0.214)
year==2012	0.762***	0.593***	0.708*	0.708***
	(0.128)	(0.146)	(0.373)	(0.203)
year==2013	0.710***	0.540***	0.645*	0.646***
	(0.120)	(0.150)	(0.358)	(0.194)
year==2014	0.766***	0.570***	0.680*	0.681***
	(0.118)	(0.152)	(0.378)	(0.201)
year==2015	0.842***	0.730***	0.827**	0.827***
	(0.116)	(0.161)	(0.341)	(0.191)
year==2016	0.874***	0.683***	0.780**	0.780***
	(0.132)	(0.182)	(0.356)	(0.197)
Constant	-1.402***	-1.299***	-	-
	(0.082)	(0.131)	-	-
Observations	660	403	403	403
R-squared	0.717	0.709	0.701	0.701
Number of regcode	15	15	15	15
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

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 "$***$"$p < 0.01$, "$**$"$p < 0.05$, "$*$"$p < 0.1$.

Table C3: **Complete estimation results using GMOS in place of G: OLS vs. 2SLS regressions**

	$\ln y$	$\ln y$	$\ln Y/X$	$\ln Y/X$
	OLS+PSW	2SLS+PSW	OLS+PSW	2SLS+PSW
	(1)	(2)	(3)	(4)
Dependent variable: lny or $\ln Y/X$				
lnk	0.716***	0.478***	-	-
	(0.120)	(0.152)	-	-
$GMOS$	-0.960	-2.118***	0.203	0.093
	(0.601)	(0.777)	(0.162)	(0.194)
$lnk * GMOS$	-1.078**	-1.989***	-	-
	(0.488)	(0.625)	-	-
year==1974	-0.047	-0.028	0.004	0.005
	(0.051)	(0.117)	(0.068)	(0.062)
year==1975	-0.078	-0.053	-0.040	-0.039
	(0.056)	(0.118)	(0.093)	(0.085)
year==1976	-0.107	-0.054	-0.033	-0.031
	(0.071)	(0.120)	(0.121)	(0.110)
year==1977	-0.081	-0.004	0.048	0.050
	(0.075)	(0.121)	(0.118)	(0.107)
year==1978	-0.053	0.038	0.095	0.096
	(0.080)	(0.124)	(0.132)	(0.120)
year==1979	-0.036	0.066	0.159	0.160
	(0.088)	(0.122)	(0.128)	(0.117)
year==1980	-0.028	0.087	0.194	0.195
	(0.101)	(0.134)	(0.136)	(0.125)
year==1981	-0.014	0.081	0.203*	0.204**
	(0.099)	(0.121)	(0.113)	(0.103)
year==1982	0.036	0.148	0.273**	0.274**
	(0.104)	(0.129)	(0.122)	(0.112)
year==1983	-0.033	0.089	0.203	0.205
	(0.108)	(0.141)	(0.140)	(0.127)
year==1984	0.063	0.186	0.301**	0.303**
	(0.123)	(0.131)	(0.134)	(0.122)
year==1985	0.021	0.126	0.296**	0.297**
	(0.134)	(0.130)	(0.135)	(0.123)
year==1986	0.092	0.222*	0.370**	0.371***
	(0.122)	(0.132)	(0.142)	(0.129)
year==1987	0.122	0.264*	0.409**	0.410***
	(0.123)	(0.137)	(0.144)	(0.132)

Table C3 continued: **Complete estimation results using GMOS in place of G: OLS vs. 2SLS regressions**

	$\ln y$	$\ln y$	$\ln Y/X$	$\ln Y/X$
	OLS+PSW	2SLS+PSW	OLS+PSW	2SLS+PSW
	(1)	(2)	(3)	(4)
Dependent variable: lny or $\ln Y/X$				
year==1988	0.141	0.294**	0.438**	0.440***
	(0.118)	(0.141)	(0.149)	(0.136)
year==1989	0.203	0.338**	0.491***	0.492***
	(0.119)	(0.133)	(0.147)	(0.134)
year==1990	0.251**	0.370***	0.544***	0.544***
	(0.102)	(0.130)	(0.118)	(0.108)
year==1991	0.249**	0.391***	0.556***	0.556***
	(0.094)	(0.135)	(0.111)	(0.101)
year==1992	0.287**	0.459***	0.598***	0.599***
	(0.107)	(0.150)	(0.124)	(0.113)
year==1993	0.237*	0.396***	0.560***	0.561***
	(0.116)	(0.146)	(0.134)	(0.122)
year==1994	0.258*	0.423***	0.563***	0.564***
	(0.125)	(0.146)	(0.141)	(0.129)
year==1995	0.247*	0.410***	0.549***	0.551***
	(0.128)	(0.148)	(0.149)	(0.136)
year==1996	0.308**	0.484***	0.639***	0.641***
	(0.128)	(0.154)	(0.148)	(0.135)
year==1997	0.326**	0.508***	0.663***	0.666***
	(0.145)	(0.160)	(0.157)	(0.144)
year==1998	0.364**	0.551***	0.711***	0.716***
	(0.147)	(0.173)	(0.175)	(0.160)
year==1999	0.334*	0.517***	0.692***	0.699***
	(0.170)	(0.183)	(0.184)	(0.170)
year==2000	0.306*	0.453**	0.688***	0.695***
	(0.152)	(0.185)	(0.158)	(0.144)
year==2001	0.329**	0.514***	0.709***	0.718***
	(0.144)	(0.171)	(0.162)	(0.149)
year==2002	0.295*	0.481***	0.665***	0.674***
	(0.160)	(0.172)	(0.178)	(0.165)
year==2003	0.285	0.460***	0.670***	0.679***
	(0.170)	(0.169)	(0.186)	(0.172)
year==2004	0.318*	0.512***	0.727***	0.736***
	(0.169)	(0.177)	(0.177)	(0.164)
year==2005	0.316*	0.543***	0.712***	0.723***
	(0.175)	(0.199)	(0.203)	(0.190)

Table C3 continued: **Complete estimation results using GMOS in place of G: OLS vs. 2SLS regressions**

	$\ln y$	$\ln y$	$\ln Y/X$	$\ln Y/X$
	OLS+PSW	2SLS+PSW	OLS+PSW	2SLS+PSW
	(1)	(2)	(3)	(4)
Dependent variable: lny or $\ln Y/X$				
year==2006	0.291*	0.542***	0.697***	0.708***
	(0.153)	(0.205)	(0.190)	(0.177)
year==2007	0.321*	0.596***	0.761***	0.774***
	(0.158)	(0.214)	(0.209)	(0.195)
year==2008	0.260	0.494**	0.686***	0.700***
	(0.150)	(0.201)	(0.197)	(0.183)
year==2009	0.355**	0.640***	0.781***	0.796***
	(0.142)	(0.223)	(0.214)	(0.200)
year==2010	0.279*	0.591***	0.728***	0.743***
	(0.158)	(0.228)	(0.204)	(0.191)
year==2011	0.295*	0.586***	0.744***	0.763***
	(0.158)	(0.222)	(0.184)	(0.174)
year==2012	0.268	0.560**	0.762***	0.778***
	(0.156)	(0.229)	(0.177)	(0.162)
year==2013	0.238	0.534**	0.697***	0.711***
	(0.166)	(0.228)	(0.170)	(0.155)
year==2014	0.240	0.552**	0.733***	0.749***
	(0.168)	(0.237)	(0.184)	(0.169)
year==2015	0.382**	0.687***	0.875***	0.888***
	(0.177)	(0.228)	(0.183)	(0.166)
year==2016	0.386*	0.691***	0.828***	0.841***
	(0.194)	(0.247)	(0.200)	(0.181)
Constant	0.178	-	-1.319***	-
	-	(0.234)	-	(0.136)
Observations	403	403	403	403
R-squared	0.873	0.858	0.687	0.686
Number of regcode	15	15	15	15
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

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

Table C4: **Estimation Results Models (11) and (12)**

	G	G	GMOS	GMOS
	$\ln y$	$\ln AP$	$\ln y$	$\ln AP$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln Y/X$				
$\ln k_{it}$ (or β_0)	-0.100	0.109	-	-
	(0.205)	(0.155)	-	-
G_{it} (or α)	0.722***	-	0.509**	-
	(0.152)	-	(0.204)	-
$G_{it} * \ln k_{it}$ (or β)	-0.402***	-	-	-
	(0.102)	-	-	-
R&D Stock	-0.090	0.104	-0.024	0.091
	(0.086)	(0.073)	(0.080)	(0.071)
Crop Value Share	0.614	-0.423	0.551	-0.379
	(0.445)	(0.303)	(0.419)	(0.343)
Weather Index	0.013	0.022	-0.003	0.015
	(0.070)	(0.063)	(0.061)	(0.065)
year==1974	-0.068	-0.000	-0.038	0.005
	(0.141)	(0.145)	(0.127)	(0.147)
year==1975	-0.094	-0.052	-0.055	-0.043
	(0.145)	(0.145)	(0.128)	(0.145)
year==1976	-0.143	-0.048	-0.063	-0.034
	(0.143)	(0.142)	(0.132)	(0.141)
year==1977	-0.105	0.022	-0.011	0.037
	(0.147)	(0.131)	(0.142)	(0.132)
year==1978	-0.062	0.065	0.032	0.078
	(0.151)	(0.132)	(0.152)	(0.133)
year==1979	-0.048	0.117	0.062	0.134
	(0.159)	(0.131)	(0.158)	(0.129)
year==1980	-0.029	0.157	0.078	0.169
	(0.164)	(0.141)	(0.172)	(0.140)
year==1981	-0.010	0.158	0.078	0.171
	(0.157)	(0.135)	(0.160)	(0.134)
year==1982	0.042	0.226*	0.142	0.240*
	(0.164)	(0.135)	(0.172)	(0.135)
year==1983	-0.036	0.154	0.080	0.171
	(0.175)	(0.149)	(0.186)	(0.149)
year==1984	0.051	0.251*	0.171	0.269**
	(0.174)	(0.133)	(0.178)	(0.130)
year==1985	0.053	0.238*	0.127	0.250*
	(0.165)	(0.136)	(0.175)	(0.134)

Table C4 continued: **Estimation Results Models (11) and (12)**

	G	G	GMOS	GMOS
	$\ln y$	$\ln AP$	$\ln y$	$\ln AP$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln Y/X$				
year==1986	0.110	0.305**	0.220	0.322**
	(0.182)	(0.131)	(0.190)	(0.128)
year==1987	0.162	0.343***	0.266	0.356***
	(0.186)	(0.130)	(0.199)	(0.128)
year==1988	0.167	0.365***	0.294	0.384***
	(0.197)	(0.133)	(0.209)	(0.129)
year==1989	0.250	0.423***	0.341*	0.435***
	(0.185)	(0.133)	(0.197)	(0.132)
year==1990	0.312*	0.473***	0.375**	0.482***
	(0.174)	(0.139)	(0.189)	(0.138)
year==1991	0.311*	0.485***	0.392*	0.494***
	(0.186)	(0.139)	(0.204)	(0.138)
year==1992	0.327	0.519***	0.456**	0.536***
	(0.209)	(0.140)	(0.227)	(0.137)
year==1993	0.277	0.476***	0.392*	0.494***
	(0.208)	(0.142)	(0.223)	(0.137)
year==1994	0.241	0.474***	0.415*	0.502***
	(0.217)	(0.144)	(0.222)	(0.136)
year==1995	0.087	0.432**	0.394*	0.489***
	(0.266)	(0.170)	(0.224)	(0.139)
year==1996	0.184	0.536***	0.462**	0.586***
	(0.248)	(0.162)	(0.229)	(0.137)
year==1997	0.210	0.551***	0.488**	0.605***
	(0.257)	(0.168)	(0.241)	(0.139)
year==1998	0.146	0.580***	0.523**	0.658***
	(0.289)	(0.192)	(0.253)	(0.144)
year==1999	0.149	0.556***	0.489*	0.634***
	(0.297)	(0.205)	(0.267)	(0.157)
year==2000	0.051	0.538**	0.428	0.629***
	(0.316)	(0.214)	(0.261)	(0.149)
year==2001	0.119	0.550***	0.496*	0.643***
	(0.319)	(0.211)	(0.265)	(0.143)
year==2002	0.106	0.512**	0.461*	0.601***
	(0.314)	(0.212)	(0.263)	(0.149)
year==2003	0.102	0.518**	0.437*	0.605***
	(0.312)	(0.213)	(0.257)	(0.152)

Table C4 continued: **Estimation Results Models (11) and (12)**

	G	G	GMOS	GMOS
	$\ln y$	$\ln AP$	$\ln y$	$\ln AP$
	(1)	(2)	(3)	(4)
Dependent variable: $\ln y$ or $\ln Y/X$				
year==2004	0.161	0.582***	0.482*	0.665***
	(0.315)	(0.208)	(0.272)	(0.150)
year==2005	0.181	0.554**	0.526*	0.643***
	(0.336)	(0.224)	(0.302)	(0.166)
year==2006	0.166	0.539**	0.524*	0.627***
	(0.341)	(0.218)	(0.316)	(0.159)
year==2007	0.170	0.610***	0.560*	0.702***
	(0.360)	(0.233)	(0.326)	(0.164)
year==2008	0.117	0.534**	0.461	0.625***
	(0.350)	(0.226)	(0.312)	(0.157)
year==2009	0.227	0.626**	0.608*	0.720***
	(0.374)	(0.243)	(0.340)	(0.175)
year==2010	0.162	0.567**	0.553	0.664***
	(0.382)	(0.245)	(0.354)	(0.168)
year==2011	0.175	0.584**	0.547	0.689***
	(0.384)	(0.243)	(0.342)	(0.154)
year==2012	0.173	0.610***	0.511	0.710***
	(0.382)	(0.233)	(0.347)	(0.152)
year==2013	0.175	0.531**	0.503	0.626***
	(0.379)	(0.225)	(0.354)	(0.155)
year==2014	0.218	0.557**	0.528	0.656***
	(0.394)	(0.232)	(0.371)	(0.161)
year==2015	0.340	0.710***	0.659*	0.799***
	(0.388)	(0.230)	(0.360)	(0.173)
year==2016	0.340	0.662***	0.657*	0.752***
	(0.406)	(0.251)	(0.384)	(0.201)
$GMOS$	-	-	-2.158***	0.080
	-	-	(0.861)	(0.086)
$\ln k * GMOS$	-	-	-2.087***	-
	-	-	(0.694)	-
Number of Observations	403	403	403	403
R-squared	0.847	0.708	0.861	0.690
Number of countries	15	15	15	15
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

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

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