The Unexpected Impact of Genetically Modified Crops on Global Carbon Emissions

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Abstract

Genetically modified (GM) crops are expected to reduce agricultural carbon emissions, which account for approximately 30% of global carbon emissions, by reducing the use of high-emission production inputs. However, upon examining the gradual roll-out of GM crops across countries, we find that GM crops have increased total agricultural carbon emissions by 7.4% and increased the carbon-emission intensity of crops by 9.4%. A key reason is that GM crops have expanded cultivation into marginal lands, which require more fertilizer and energy inputs. While exporting GM crops to non-GM countries could reduce the global carbon-emission impact of GM crops, a large portion of GM crops is used for domestic livestock production, which further increases carbon emissions. Policies that restrict GM crops to the lands most suitable for them and encourage the export of GM crops could help mitigate the impact of GM crops on global carbon emissions.

Keywords: Genetically modified crops, agricultural carbon emissions, agricultural technology, crop yield
JEL: Q16, Q54, O13, O50

1 Introduction

Climate change has led to substantial damage and induced panic globally (Tol, 2009; Carleton & Hsiang, 2016; Nordhaus, 2019). Substantial evidence suggests that anthropogenic greenhouse gas emissions (carbon emissions hereafter) are the principal cause of climate change (Crowley, 2000; Solomon *et al.*, 2009). In 2021, carbon emissions from global agrifood systems reached 16 billion tonnes, representing a 14% increase since 2001 and accounting for 30% of total global anthropogenic carbon emissions (FAO, 2023). Exploring ways to reduce agricultural carbon emissions is crucial for mitigating climate change.

Advances in agricultural technologies that reduce high-emission inputs and minimize arable land usage may reduce agricultural carbon emissions. Genetic modification of crops is one such technology. Genetically modified (GM) crops, initially developed to boost crop resilience and agricultural productivity, are believed to mitigate agricultural carbon emissions by reducing production inputs and conserving land (Qaim & Zilberman, 2003; Klümper & Qaim, 2014). Over the past two decades, the harvested area of GM crops has grown at an annual rate of 8.6% (ISAAA, 2020), and by 2023, it accounted for 23.7% of the harvested area of all field crops worldwide (AgbioInvestor, 2023). Studies based on field trials (e.g., Carpenter, 2010) and scientific emission models (e.g., Brookes, 2022) suggest that GM crops could reduce carbon emissions because the pest-resistant and herbicide-tolerant traits of GM crops contribute to reductions in pesticide, energy, and land inputs per unit of crop output.

However, this prediction is inconsistent with the observed significant growth in agricultural carbon emissions over the period of rapid GM crop adoption (FAO, 2023). When examining the effect of GM crops on agricultural carbon emissions based on data from 1985 to 2018 for 145 countries, our difference-in-differences (DID) estimates suggest that the adoption of GM crops increased the total agricultural carbon emissions by 7.3% and increased carbon emissions per crop yield by 9.4%. Event studies and various robustness checks confirm that this finding represents a causal effect and is not driven by preexisting trends or confounding factors.

We develop a conceptual model to help understand why the adoption of GM crops increases carbon emissions. The model is built on the fact that the two primary sources of agricultural carbon emissions are production inputs and land use changes (See subsection 2.1 for details). It assumes a representative farmer selects the amount of land

and other variable inputs to maximize agricultural income. The adoption of GM crops is assumed to increase the efficiency of the variable inputs. We examine the effect under three scenarios: fixed land area, flexible land area with constant land quality, and flexible land area with declining land quality. The adoption of GM crops is predicted to increase total carbon emissions in each of the three scenarios by increasing the production inputs and to increase carbon emissions per yield in the last scenario by extending production to marginal lands with lower quality; the effect on carbon emissions per yield is negative in the first scenario and ambiguous in the second scenario. The intuition behind the predicted impact on total carbon emissions is the widely observed Jevons paradox (Jevons, 1866): as technological progress improves the efficiency of production inputs, the total consumption of that input may actually increase rather than decrease. The predicted impacts on carbon emissions per yield depend critically on extending production to marginal lands that require more high-emission inputs.

We present evidence supporting the predicted mechanisms of the effect of GM crops on carbon emissions. First, we show that the adoption of GM varieties increased the yield and harvested area of major GM crops by 13.8% and 15.0%, respectively. Second, we find that GM crops increased per area input of fertilizer and energy, two major sources of carbon emissions, by 23.3% and 8.0%, respectively. Third, GM crops increased total crop area, encouraged multiple cropping, crowded out non-GM crops, and reduced tree cover. Fourth, GM crops reduced the average quality of the land cultivating GM crops. Finally, we show that the effect on carbon emissions per yield is larger in countries more likely to reclaim low-quality marginal land (i.e., countries with lower farmland per capita and lower GDP per capita). Therefore, a potential way to reduce the impact of GM crops on carbon emissions is to limit their cultivation to the most suitable land for them.

Finally, we investigate the potential effect of agricultural trade on mitigating the impact of GM crops on carbon emissions. We show that GM countries on average have a lower carbon emissions per crop yield than non-GM countries, suggesting that the carbon-emission effect can be partly offset by exporting GM crops. However, only one-third of the additional crop output is directly exported and the remainder is used for domestic consumption, especially for livestock production. The substantial increase in domestic livestock production further increases carbon emissions, and this effect cannot be mitigated by exporting livestock because non-GM countries on average have a lower carbon-emission intensity in livestock production. Therefore, encouraging the export of crops from GM countries to non-GM countries with higher carbon-emission intensity could also mitigate the impact on global carbon emissions.

This paper contributes to the literature on evaluating the impact of GM crops. Many studies have examined the impact of GM crops on yield (Qaim & De Janvry, 2003), farmer health (Huang *et al.*, 2002), consumer willingness to pay (Kimenju & De Groote, 2008), production inputs (Ahmed *et al.*, 2021), land use change (Villoria, 2019), structural transformation (Bustos *et al.*, 2016), grain trade (Nes *et al.*, 2022), and biodiversity (Noack *et al.*, 2024). Only a small number of studies examined the effect of GM crops on carbon emissions based on field trials or scientific emission models (e.g., Carpenter, 2010; Brookes, 2022). For a given farmland area, these studies generally suggest that GM crops reduced carbon emissions by increasing the efficiency of production inputs. However, our study illustrates that when farmers are allowed to expand the production scale, GM crops could substantially increase the total amount and intensity of agricultural carbon emissions. The inconsistency between our findings and previous field-trial based studies can be explained by the well-known Jevons paradox (Jevons, 1866).

This paper also contributes to the literature on examining the determinants of agricultural carbon emissions. Existing studies have examined the effect of agricultural productivity (Jones & Sands, 2013), land savings (Hong *et al.*, 2022), land use change (Havlík *et al.*, 2013), land management (Baker *et al.*, 2013), irrigation (Zhao *et al.*, 2018), and agricultural subsidies (Laborde *et al.*, 2021) on agricultural carbon emissions. Our study complements the literature by examining one of the most important agricultural technology progress, genetic modification of crops, on agricultural carbon emissions. An important implication of our study is that technology progress not necessarily reduce carbon emissions, even when the technology progress improves the efficient of the high-emission inputs.

The remainder of the study proceeds as follows. Section 2 provides the background of this study, Section 3 presents the conceptual model, Section 4 describes the data and the empirical strategy, Section 5 presents the main results, Section 6 examines the mechanisms of the effect, and Section 7 concludes.

2 Background

2.1 Agricultural carbon emissions

In 2021, the carbon emissions from global agrifood systems reached 16 billion tonnes, representing a 14% increase since 2001 and accounting for 30% of total global anthropogenic carbon emissions (FAO, 2023). Within the agrifood systems, livestock (including enteric fermentation, manure management, and pasture management) account for 31% of emissions, crop production accounts for 27%, land use (including land use change, cultivated organic soils, and savanna burning) accounts for 24%, and the supply chain accounts for the remaining 18% (Ritchie, 2019).

Agricultural carbon emissions consist of methane (CH_4, 40–45%), nitrous oxide (N_2O, 40–50%), and carbon dioxide (CO_2, 10–15%). CH_4 is mostly released through enteric fermentation in livestock and manure management, N_2O arises from synthetic fertilizer application and manure in soils and rice cultivation, while CO_2 is primarily linked to fuel combustion and land-use changes (FAO, 2020). Emissions of CH_4, N_2O, and CO_2 are usually converted into CO_2 equivalents using their global warming potentials, making it possible to aggregate different gases into a single emissions measure.[1]

The most widely used agricultural carbon emission dataset is constructed by FAO (`https://www.fao.org`). FAO calculates agricultural carbon emissions based on the IPCC Tier 1 method (Eggleston *et al.*, 2006; FAO, 2023).[2] To make the carbon emission data comparable across countries, the IPCC method calculates the emission by combining default emission factors with agricultural production inputs and activity data. Specifically, for each input or activity, such as fertilizer application, fossil fuel consumption, or crop residue burning, the amount of input or activity is multiplied by the corresponding emission factor to estimate the carbon emissions. In addition, FAO also incorporates detailed adjustments to emission factors to account for specific conditions. For example, when estimating emissions from perennial crops, FAO makes adjustments for different crop types and climate conditions. This ensures that while the core method relies on standard emission factors, the calculations are tailored to

[1] The commonly used global warming potentials for each gas are from the IPCC Fifth Assessment Report: $CO_2 = 1\,CO_2$, $CH_4 = 28\,CO_2$, and $N_2O = 265\,CO_2$.

[2] More details on the calculation process can be found at `https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html`.

capture specific agricultural practices and environmental conditions.

Note that the emission factors adopted by FAO are the same for the GM and non-GM varieties of the same crop. This fact avoids the concern that carbon emission effect of GM crops is artificially caused by the differences in the calculation process. Appendix Table A1 summarizes the data sources, main steps, and factor adjustments of the carbon emission calculation adopted by FAO. Appendix A.3 presents an example to illustrate how FAO calculates the carbon emissions from a given crop.

2.2 Genetically modified crops

Agricultural GM technology began in the early 1980s with the creation of the first GM plant, tobacco, in 1983. This breakthrough led to the commercialization of GM crops, with the 'Flavr Savr' tomato being the first approved for sale in 1994 (James, 2013). In 1996, Monsanto introduced Roundup Ready soybean, engineered for glyphosate resistance, which improved weed control without harming the crop (Bruening *et al.*, 2000). That same year, Bt corn was commercialized, designed to produce a bacterial toxin that targeting pests while being safe for humans. Since then, GM crops such as soybean, maize, cotton, and rapeseed have been developed for traits like pest resistance and herbicide tolerance. These innovations have reduced the need for pesticides and herbicides, cutting production costs and environmental impact (Carpenter, 2010). Appendix Table A2 summarizes the key characteristics of each of the major GM crops.

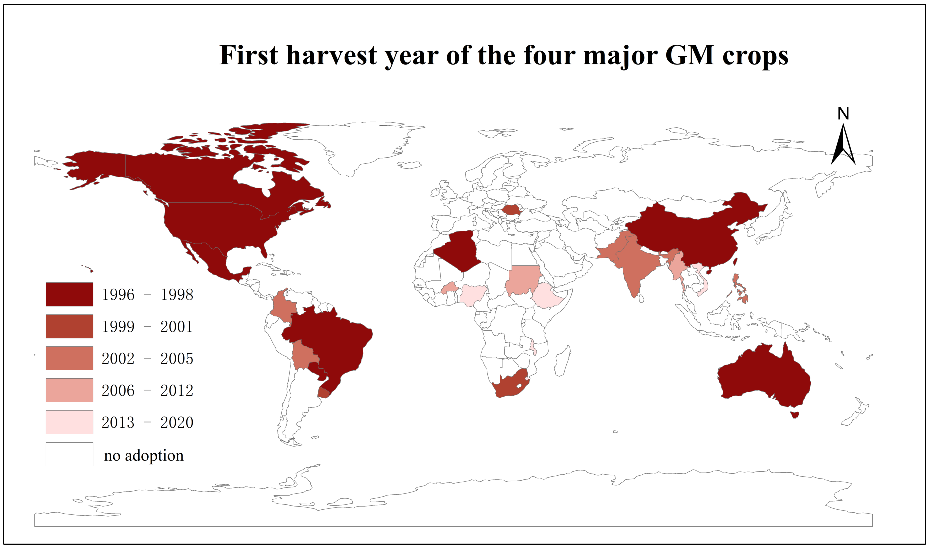

Figure 1: First harvest year of the four major GM crops in each country
Notes: This figure shows the first harvest year of the four major GM crops (maize, soybean, cotton, and rapeseed) across countries. The four major GM crops account for 98% of global GM crop production.

The global acreage of GM crops expanded swiftly, from 1.7 million hectares in 1996 to over 190 million hectares by 2018. Figure 1 shows that by 2018, 29 major agricultural production countries, accounting for 67% of global harvested area of field crops, have adopted at least one of the four most widely cultivated GM crops (maize, soybean, cotton, and rapeseed). The four major GM crops account for 98% of global GM crop production (ISAAA, 2020). Appendix Figure A1 presents the adoption year and adoption rate of each of the four major GM crops in each country. Since the advent of GM technology, the global production of soybean and maize has increased by approximately 330 million tons and 595 million tons, respectively (Brookes, 2022). From 1996 to 2018, farmers worldwide realized a cumulative additional income of $225 billion from the use of GM technology. Although GM crops hold significant potential and are widely utilized, they remain constrained by prohibitions. Hansen & Wingender (2023) find that the global benefits derived from the adoption of GM crops have been limited to only one-third of their potential now.

2.3 Trends in crop area, land quality, and carbon emissions

This subsection shows that the trends in crop area, land quality, and carbon emissions are consistent with the main argument of this study that the adoption of GM crops extends the crop cultivation to marginal lands with lower quality, which in turn increase agricultural carbon emissions.

Expanding crop area. Figure 2 presents a significant increasing trend in the global share of the harvested area of the four major GM crops after 1996, the year when GM varieties of these crops become available for commercialization. This increasing trend does not exist before 1996. The share of the four GM crops increased from 15.4% in 1996 to 20.7% in 2018. This increase is mainly driven by maize and soybean, the two major GM field crops. Similar but more significant trends are observed in Figure 6 when focusing on the GM countries.

Figure 2: Changes in the share of the four major GM crops in global crop harvested area

Notes: The gray dashed line represents the year when GM crops were first commercially cultivated.

Declining land quality. Figure 3 presents the grid-level land expansion and land quality decline from 2000 to 2010 for soybean and maize, the two GM crops that experienced significant land expansions. The $9.25km \times 9.25km$ grid-level data for each crop are derived from FAO's GAEZ database (FAO, 2021) and are only available for 2000 and 2010. Panels A and B show that the cultivated area of these two crops increased substantially over this period, consistent with what is presented in Figure 6. Panels C and D present the distribution of the grid-level land quality in each year. We find an increase in the share of low-quality land and a reduction in the share of high-quality land from 2000 to 2010 for both crops. The GAEZ data measures land quality by crop-specific attainable yield, calculated by combining climate, soil, and terrain factors of the land. As the attainable yield is time invariant, the changes in land quality come only from changes in the cultivated area.

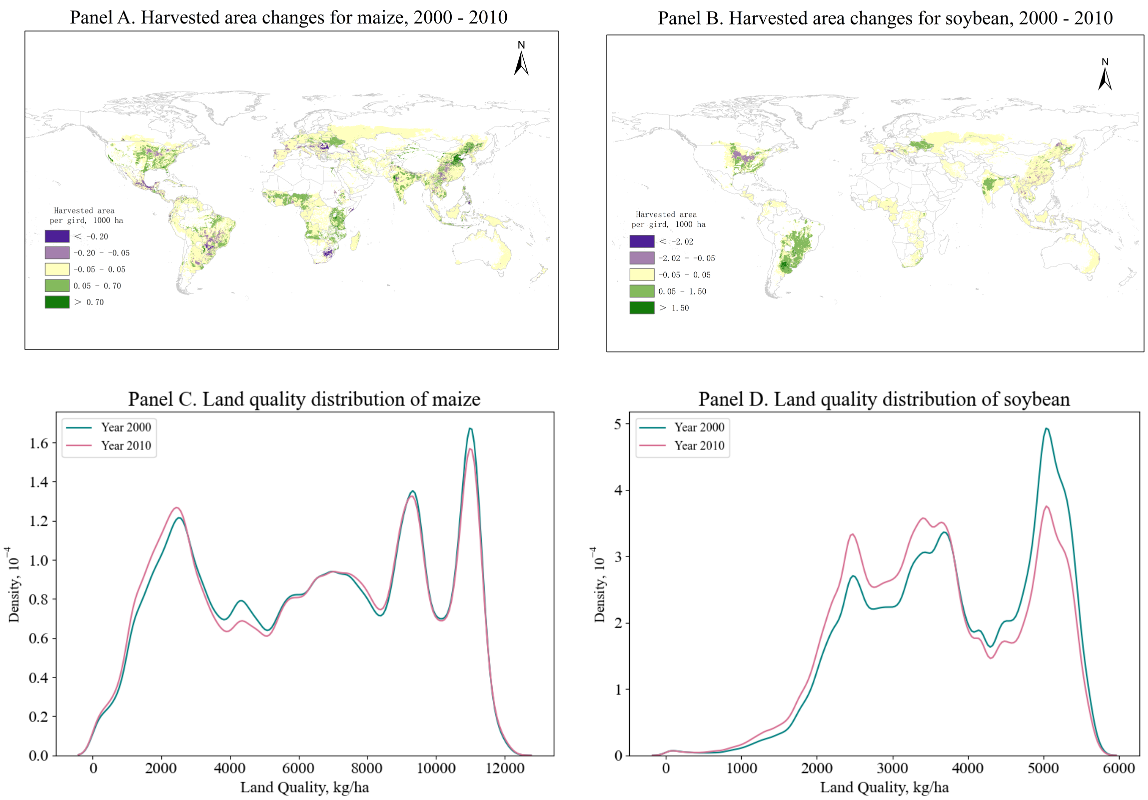

Figure 3: Grid-level changes in the harvested area and land quality for maize and soybean

Notes: Panels A and B present the grid-level changes in the harvested area for soybean and maize from 2000 to 2010. Panels C and D present the distribution of the grid-level land quality in 2000 and 2010 for countries that cultivated the GM varieties of these two crops. The land quality is measured by the crop-specific attainable yield, which is derived from the FAO's GAEZ database.

Increasing carbon emissions. Figure 4 shows that country-level carbon emissions increased significantly for the crop sector (Panel A) and for the whole agricultural sector (Panel B) following the adoption of GM crops. Specifically, we plot the distribution of country-level log carbon emissions in both 1996 and 2018. We use the data from all countries instead of only GM countries considering that carbon emissions of non-GM countries could also be affected through crop trade. We find significant rightward shift in the distribution of carbon emissions from 1996 to 2018, suggesting a significant positive effect of GM crops on global carbon emissions. Similar trends in crop-level carbon emissions per area are presented in Appendix Figure A2.

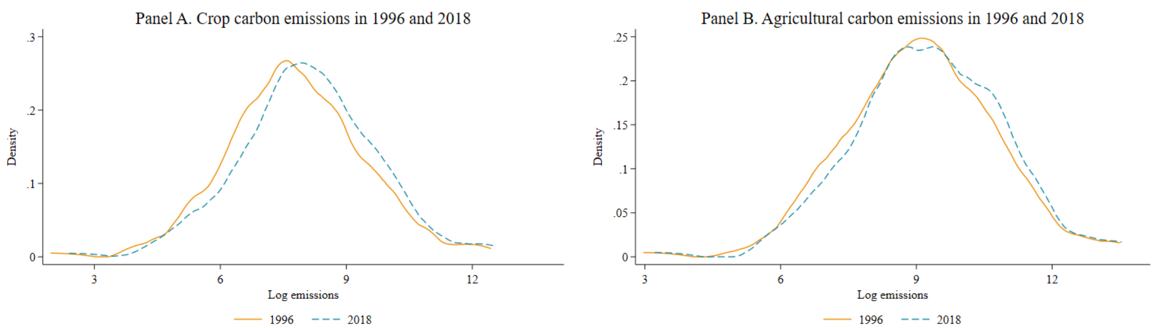

Figure 4: Distributions of agricultural carbon emissions in 1996 and 2018

Notes: The figure presents the distributions of country-level log total carbon emissions for the crop sector and the entire agricultural sector in 1996 and 2018.

3 Conceptual Framework

3.1 Potential channels of the effect

Figure 5 presents the potential channels for GM crops to affect agricultural carbon emissions. The effect channels can be roughly classified as direct effect channels and indirect effect channels. We will examine each of these channels in our empirical analysis. A key implication of these channels for our empirical analysis is that, as GM crops could affect the carbon emissions of non-GM crops and non-crop agricultural production, one should focus on the entire agricultural sector when examining the effect of GM crops on carbon emissions.

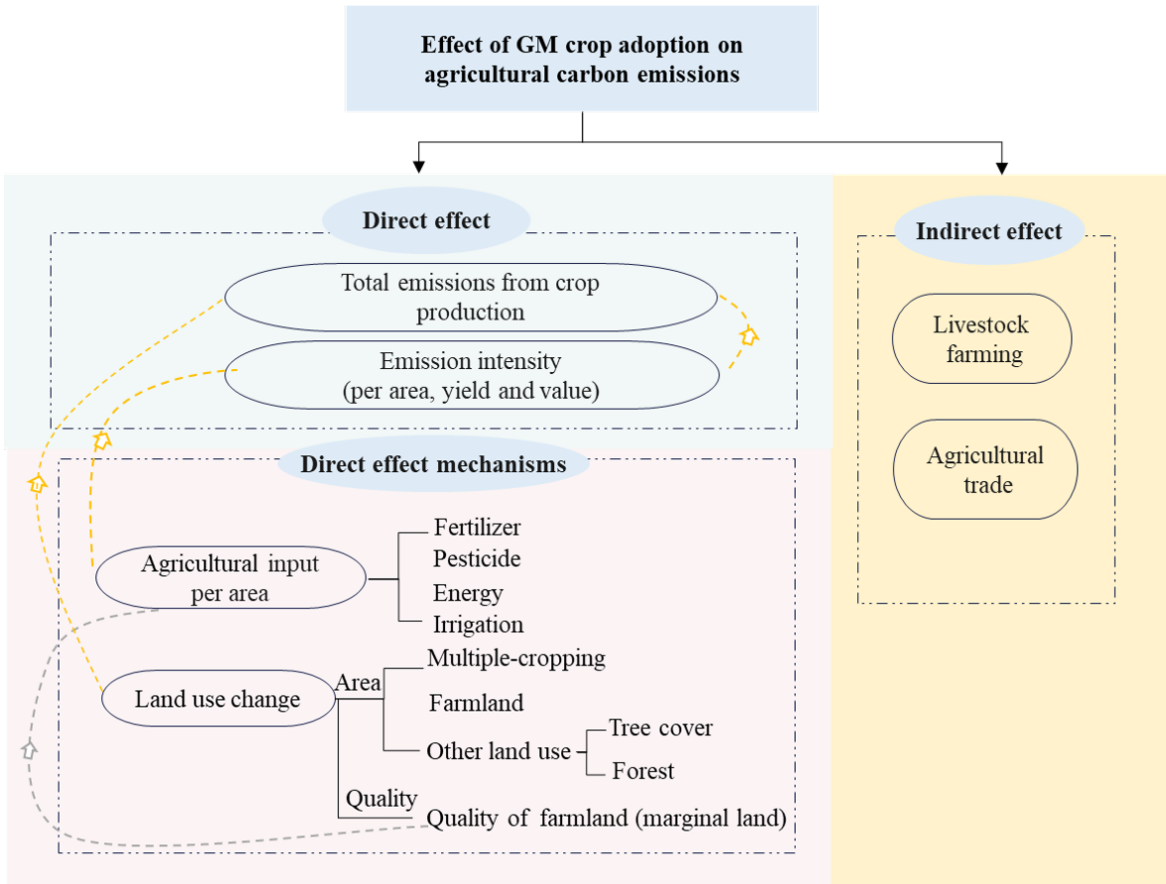

Figure 5: Mechanisms of the effect of GM crops on carbon emissions

Direct effect channels. GM crops could affect total agricultural carbon emissions and the emission intensity by altering the production inputs and types of land use. Compared with non-GM crops, GM crops may require different amounts of fertilizers, pesticides, and energy (for machinery and irrigation) (Noack *et al.*, 2024), and these changes could affect agricultural carbon emissions. In addition, higher profit from GM crops may convert other types of agricultural lands, such as forest and grasslands, into crop production and reallocate land from other crops to GM crops (Carreira *et al.*, 2024). Given that different types of land use and crop types have varying carbon emissions, the GM-induced land use change could affect carbon emissions (Searchinger *et al.*, 2018). Higher profit from GM crops may also lead farmers to increase multiple cropping, reduce fallow, and utilize marginal lands for production (Klümper & Qaim, 2014). These changes could lower the land quality and increase production inputs and carbon emissions.

Indirect effect channels. GM crops have the potential to indirectly affect carbon emissions through livestock production and agricultural trade. Crops, along with their stalks, are major inputs in livestock production (Van Eenennaam & Young, 2014).[3] The adoption of GM crops may reduce the cost and increase the output of livestock production. Given that livestock production accounts for more than one-third of agricultural carbon emissions, the impact of GM crops on livestock production could affect total agricultural carbon emissions. In addition, changes in the output and price of crops and livestock could affect agricultural trade. Since agricultural carbon-emission intensity varies across countries, the GM-induced changes in agricultural trade could also affect global agricultural carbon emissions (Nguyen *et al.*, 2021).

3.2 A simple theoretical model

We develop a simple model to illustrate the direct effect of GM crops on agricultural carbon emissions. To separate the effects from input adjustment, land expansion, and land quality decline, the model examines the effect in each of the following three scenarios: (1) fixed land area; (2) flexible land area with constant land quality; and (3) flexible land area with declining land quality. The model focuses only on the direct effect, which is also the focus of our empirical analysis.

3.2.1 Model setup

A representative farmer aims to maximize agricultural revenue through the cultivation of a single crop. Agricultural production depends on farmland T and a composite input E , which includes fertilizers, pesticides, energy, irrigation, and labor. The adoption of GM crops is a factor-augmenting technical progress (Bustos *et al.*, 2016) and increases the efficiency of the composite input by a factor of $\theta > 1$, reflecting the fact that GM crops save various inputs such as pesticides, energy, and labor (Qaim & Zilberman, 2003; Klümper & Qaim, 2014). The production function is given by:

$$Y = A[\theta E]^{\beta}[q(T)T]^{1-\beta}, \tag{1}$$

[3] Maize and soybean are major inputs in livestock production in many countries. Cottonseed can be refined into cottonseed cake for livestock feed. Stalks of these crops can be used in animal feed, providing fiber and other nutritional components.

where $0 < \beta < 1$ and A is the constant total factor productivity. The land quality function $q(T)$ captures the effect of land expansion on land quality:

$$q(T) = (\frac{T_0}{T})^{\alpha}, \quad 0 \leq \alpha < 1, \tag{2}$$

where T_0 is the initial land area managed by the farmer, T is the current land area, and α is a parameter capturing the effect of land expansion on land quality. Specifically, $\alpha = 0$ implies a constant land quality, while $\alpha > 0$ implies a declining average land quality with land expansion. The assumption of $\alpha > 0$ is consistent with the fact that the best lands are typically first used (Gollin *et al.*, 2021).

The farmer maximizes total profits:

$$\max_{E,T} \Pi = PY - w_E E - w_T T, \tag{3}$$

where P is the price of the output, and w_E and w_T are the prices of E and T, respectively. We assume that the adoption of GM crops does not affect prices; the effect of price changes will be discussed later.

We prefer to interpret farmland expansion as an expansion of harvested area because the adoption of GM crops could lead to an increase in multiple cropping (or equivalently, a reduction in seasonal fallow), which increases the harvested area for a given land area. An increase in multiple cropping has similar effects as land expansion in increasing crop output and reducing land quality. Studies suggest that increases in multiple cropping usually lead to more than proportional increases in production inputs, such as fertilizers and energy (Tilman *et al.*, 2002; Zhang *et al.*, 2013).

Total carbon emissions increase with the flexible input E and land T :

$$C = aE + bT^{\gamma}, \quad a, b > 0, \quad \gamma > 1.$$

This model setting reflects that production inputs and land use changes are the two primary sources of crop carbon emissions (subsection 2.1). We allow $\gamma > 1$ to reflect the fact that land expansion could lead to more than proportional increase in carbon emissions. Land expansion usually requires clearing vegetation, leveling the land, and improving soil quality before the production, and these activities could generate additional carbon emissions. More importantly, as mentioned above, if the land expansion takes the form of increased multiple cropping, it could lead to a more than proportional increase in production inputs; these changes are not captured by the flexible inputs E in our model setting.

We measure carbon-emission intensity by emissions per area and emissions per yield:

$$I_{area} = \frac{aE + bT^{\gamma}}{T},$$
$$I_{yield} = \frac{aE + bT^{\gamma}}{Y}.$$

3.2.2 Scenario 1: Fixed land area

In the case fixed land area (i.e., $T = T_0$), the profit maximizing condition of the farmer is:

$$PA\beta\theta^{\beta}E^{\beta-1}T_0^{1-\beta} = w_E.$$

In the equilibrium, the total carbon emissions are

$$C = a\left(\frac{w_E}{PA\beta\theta^{\beta}T_0^{1-\beta}}\right)^{\frac{1}{\beta-1}} + bT_0^{\gamma}, \tag{4}$$

and the carbon-emission intensities are

$$I_{area} = \left(\frac{w_E}{PA\beta\theta^{\beta}}\right)^{\frac{1}{\beta-1}} + bT_0^{\gamma-1}, \tag{5}$$

$$I_{yield} = \frac{aP\beta}{w_E} + \frac{b}{A}T_0^{\gamma-1}(\frac{PA\beta\theta}{w_E})^{\frac{\beta}{\beta-1}}. \tag{6}$$

As $\beta < 1$, equations (4), (5), and (6) suggest that the adoption of the GM crops (i.e., an increase in θ) increases total carbon emissions, increases carbon emissions per area, and reduces carbon emissions per yield.

Proposition 1 *For a fixed farmland area, the adoption of the GM crops increases total carbon emissions, increases carbon emissions per area, and reduces carbon emissions per yield.*

3.2.3 Scenario 2: Flexible land area but constant land quality

In the case of flexible land area but constant land quality (i.e.,$\alpha = 0$), the first order conditions with respect to E and T imply that

$$\frac{T}{E} = \frac{(1-\beta)w_E}{\beta w_T}, \quad T = \bar{T}, \quad PA\beta\theta^{\beta}E^{*\beta-1}\bar{T}^{1-\beta} = w_E, \tag{7}$$

where $\bar{T}$ is the maximum land area available for the farmer to rent in[4]. The equilibrium total carbon emissions, emissions per area, and emissions per yield are

$$C = a\left(\frac{w_E}{PA\beta\theta^{\beta}\bar{T}^{1-\beta}}\right)^{\frac{1}{\beta-1}} + b\bar{T}^{\gamma}, \tag{8}$$

$$I_{area} = \left(\frac{w_E}{PA\beta\theta^{\beta}}\right)^{\frac{1}{\beta-1}} + b\bar{T}^{\gamma-1}, \tag{9}$$

$$I_{yield} = \frac{aP\beta}{w_E} + \frac{b}{A}\bar{T}^{\gamma-1}(\frac{PA\beta\theta}{w_E})^{\frac{\beta}{\beta-1}}. \tag{10}$$

The only difference from scenario 1 is that land expansion caused by the adoption of GM crops increases total carbon emissions, emissions per area, and emissions per yield, given that $\bar{T} > T_0$ and $\gamma > 1$. The opposing effects of $\bar{T}$ and θ in equation (10) imply an ambiguous effect of GM crops on carbon emissions per yield.

Proposition 2 *For a flexible land area but constant land quality, the adoption of GM crops increases total carbon emissions and carbon emissions per area, but has an ambiguous effect on carbon emissions per yield.*

3.2.4 Scenario 3: Land quality declines as land expansion

In the case of declining land quality (i.e., $\alpha > 0$), the first order conditions imply that

$$T = \frac{(1-\alpha)(1-\beta)w_E}{\beta w_T}E. \tag{11}$$

[4]As prices are assumed to be constant, the equilibrium land area is in a corner solution that adopts all the available land. Assuming an increasing land price will avoid the corner solution but not affect the model prediction.

Let $K = \frac{(1-\alpha)(1-\beta)w_E}{\beta w_T}$, the equilibrium total carbon emissions and emission intensities are:

$$C = \frac{a}{K}T^* + bT^{*\gamma} = a(\frac{w_E}{PA\theta^\beta})^{\frac{1}{\alpha(\beta-1)}}T_0K^{\frac{1-\alpha}{\alpha}} + b(\frac{w_E}{PA\theta^\beta})^{\frac{\gamma}{\alpha(\beta-1)}}T_0^\gamma K^{\frac{\gamma}{\alpha}}, \tag{12}$$

$$I_{area} = \frac{a}{K} + bT^{*\gamma-1} = \frac{a}{K} + b(\frac{w_E}{PA\theta^\beta})^{\frac{\gamma-1}{\alpha(\beta-1)}}T_0^{1-\gamma}K^{\frac{\gamma-1}{\alpha}} \tag{13}$$

$$\begin{aligned} I_{yield} &= \left(\frac{a}{K}T^{*\alpha(1-\beta)} + bT^{*\alpha(1-\beta)+(\gamma-1)}\right)\left(\frac{K^\beta T_0^{\alpha(1-\beta)}}{A\theta^\beta}\right) \\ &= \frac{aP}{w_E} + b\left(\frac{1}{A\theta^\beta}\right)^{\frac{\gamma-1}{\alpha(\beta-1)}} T_0^{1-\gamma}\left(\frac{w_E}{P\beta}\right)^{\frac{\gamma-1+\alpha-\alpha\beta}{\alpha(\beta-1)}} K^{(\alpha-1)(1-\beta)+\gamma} \end{aligned} \tag{14}$$

Therefore, the adoption of GM crops increases total carbon emissions, emissions per area, and emissions per yield.

Proposition 3 *For flexible land area and declining land quality, the adoption of GM crops increases the total carbon emissions and carbon emissions per area and per yield.*

The last scenario is most realistic as the data show significant expansion of cropland (Figure 2) and a decline in land quality (Figure 3) after the adoption of GM crops. The first two scenarios are useful for highlighting that the expansion of cultivation to marginal lands with lower quality is the main cause of increased carbon emissions per yield; total carbon emissions and emissions per area are predicted to increase in each of the three scenarios.

3.2.5 The effect of price changes

Price changes resulting from GM crop adoption could affect production decisions and thus carbon emissions. It is most likely that GM crops reduce the price of output P and increase the prices of the flexible inputs w_E and land w_T. The above equilibrium conditions suggest that a lower output price reduces carbon emissions by reducing production. However, this does not alter the prediction of the model as long as GM crops still increase the output. Similarly, the increase in input and land prices only partially offsets the effect of GM crops on carbon emissions and is unlikely to alter the qualitative implications of the model.

4 Data and Empirical Strategy

4.1 Data

Our analysis relies on data from 145 countries from 1985 to 2018. We exclude the data after 2018 to avoid the confounding effect of COVID-19. We exclude countries with a total farmland area of less than 100,000 hectares and those that never cultivate any of the four GM crops (maize, soybean, cotton, and rapeseed). The 145 sample countries account for 99% of the global agricultural output in 2018.

4.1.1 GM crop adoption data

The GM crop adoption data for the four major GM crops are compiled by Hansen & Wingender (2023). The data contain the approval year and commercialization year of each GM crop in each country where the GM variety is adopted. The commercialization year is defined as the first year when a GM variety of the crop is first harvested and commercially marketed for human consumption or animal feed in the country. The data also contain the country-level harvested area of each GM crops in each year.

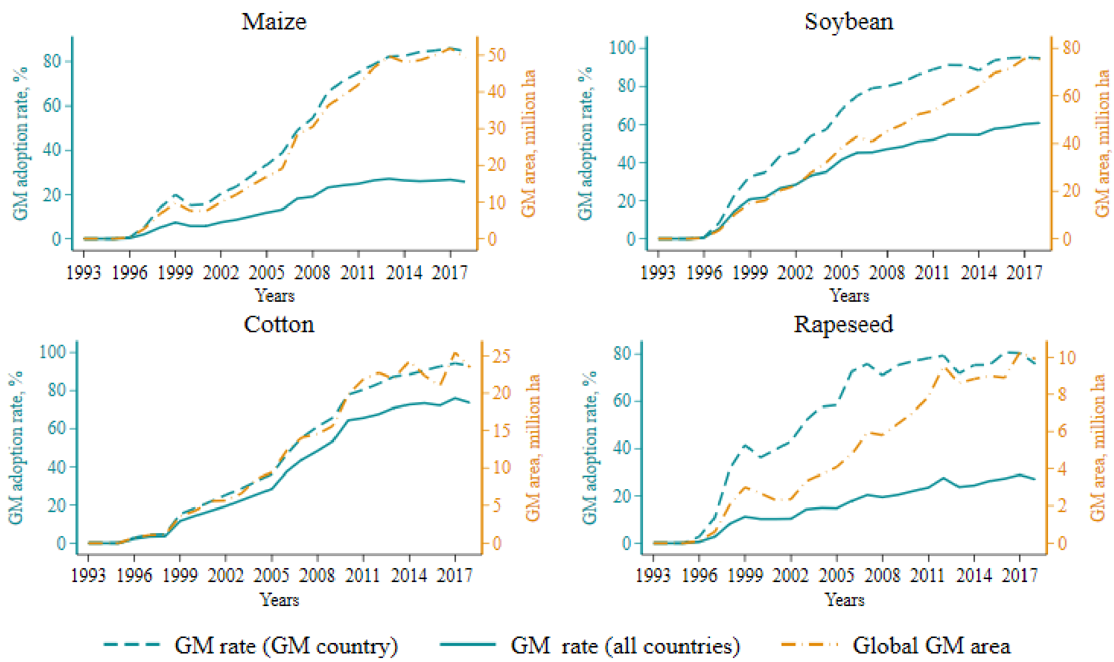

Figure 6: Adoption of the four major GM crops

Notes: This figure presents the adoption rate and area of the four major GM crops. For each crop, the solid line presents the global share of the harvested area, the dashed line presents the share of the harvested area in GM countries, and the dash-dotted lines show the global total harvested area.

Figure 6 presents the global adoption rate and area of the four major GM crops. Starting from 1996, the adoption rate in GM countries significantly increased and reaching nearly 100% for soybean and cotton and 80% for maize and rapeseed by 2018. By 2018, GM soybean and cotton accounted for more than half of the global harvested area of these two crops, while GM maize and rapeseed accounted for approximately one-fifth. Globally, the cultivated area of GM varieties reached 79 million ha for soybean, 51 million ha for maize, 24 million ha for cotton, and 10 million ha for rapeseed. Appendix Figure A1 presents the adoption rate of the major GM crops in each country.

4.1.2 Carbon emissions data

Our main analysis utilizes two country-level measures of carbon emissions: carbon emissions from all crops (i.e., crop carbon emissions) and carbon emissions from the entire agricultural sector (i.e., agricultural carbon emissions). In supplementary analysis, we will also use carbon emissions from each crop and from livestock production. All the data are available from 1985 to 2018 in the FAO dataset[5]. Our main analysis does not use crop-level emissions for two reasons. First, the Conceptual Framework suggests that focusing on specific GM crops tends to underestimate the impact on carbon emissions as the adoption of GM crops could affect the carbon emissions of non-GM crops and non-crop agricultural production. Second, the crop-level carbon emission data are only available for two major GM crops (maize and soybean) and a limited set of non-GM crops (barley, millet, oats, potatoes, rice, rye, sorghum, sugar cane, and wheat).

Crop carbon emissions refer to the carbon emissions from all crops in the country in a year. In FAO data, crop carbon emissions are also referred to as emissions from agricultural soils, which include emissions from synthetic fertilizers, manure applied to soils, manure left on pasture, crop residues, cultivation of organic soils, and synthetic fertilizers. Agricultural carbon emissions refer to emissions from all agricultural sectors, including crop production, livestock production, and forestry. All these emissions measures are calculated at the farm gate, excluding emissions from the subsequent transportation and consumption of agricultural products. More details about the construction of the FAO carbon emission data are provided in subsection 2.1.

We construct two measures of carbon-emission intensity for crop production: carbon emissions per area (hectare) and carbon emissions per yield (ton). These measures are calculated by dividing country-level total carbon emissions from crop production by crop area or by crop output. The crop area and crop output data are also derived from FAO. We also calculate crop-level emission intensity for individual crops in robustness checks. Our main analysis does not utilize the emission intensity for the entire agricultural sector as it is challenging to combine the emission intensities from different types of agricultural production.[6]

Appendix Table A3 presents the summary statistics of these emission measures. Appendix Figure A2 presents the crop-level trends of carbon emissions per area from 1985 to 2018 for crops with carbon emission data. Appendix Figure A3 presents the distribution of national total agricultural carbon emissions across the sample countries. Appendix Figure A4 presents the national carbon-emission intensity for each country.

[5] https://www.fao.org/faostat/en/#data/GT

[6] In a robustness check presented in Appendix Figure A9, we also measure the emission intensity of the entire agricultural sector by emissions per value of agricultural output.

4.1.3 Auxiliary data

Our analysis also uses crop-level data on yield and harvested area; country-level data on fertilizer, pesticide, energy use, and irrigated area; as well as country-level data on different types of agricultural land uses. The land use data include the total farmland area, the harvested area of all crops, tree cover area, and forest area. The tree cover area includes not only contiguous forested regions but also fragmented areas of tree coverage. All these data are derived from the FAO. We also use various climatic control variables: annual mean temperature, annual total precipitation, diurnal temperature range, mean cloud cover, ground frost frequency, potential evapotranspiration, vapor pressure, and number of rain days. The climate data are derived from the Climatic Research Unit, one of the most widely used observed climate datasets.

4.2 Country-level regression models

Following Hansen & Wingender (2023), we estimate the effect of GM crops based on comparing countries that adopted GM crops early and later, and countries never adopted GM crops (as the pure control group). This identification strategy critically depends on the parallel trends assumption, which states that countries adopt GM crops early and later have no preexisting differential trends in carbon emissions. We support this assumption by the following event study regression:

$$lny_{it} = \alpha + \sum_{j=2}^{J} \beta_j (Lag\, j)_{it} + \sum_{k=0}^{K} \gamma_k (Lead\, k)_{it} + \mu_i + \lambda_t + X_{it}\theta + \varepsilon_{it} \tag{15}$$

where y_{it} is the outcome variable of interest in country i and year t. The key outcome variables are crop carbon emissions, agricultural carbon emissions, and carbon-emission intensity measures. $Lag\, j$ and $Lead\, k$ are j-year lags and k-year leads relative to the event year of the country. We define the event year as the first year when the first GM crops (among the four major GM crops) are harvested in the country. In robustness checks, we will also define the event year as the approval year of the first GM crops in the country. The first lag ($j = 1$) is used as the base year and excluded from the model.

The model includes the country-fixed effects (μ_i) to account for country-specific time-invariant determinants of carbon emissions and GM crop adoption, such as agro-climatic conditions, economic incentives, and levels of public acceptance. The model includes the year-fixed effects (λ_t) to account for annual shocks common to all countries. The model also includes a vector of exogenous climatic control variables (X_{it}) to address concerns about the confounding effects from climate fluctuations.[7] The error term (ε_{it}) is clustered at the region-year level to address the potential bias in the error term caused by spatial correlation and autocorrelation.[8] To assign greater weight to countries with more agricultural production, we estimate the model using country-level harvested area as weight.

As presented in Figure 7, the event-study estimates suggest no evidence of preexisting differential trends. This finding is not surprising since the timing of GM crop adoption is unlikely to be affected by carbon emissions and their determinants. The timing of GM crop adoption is determined by factors such as domestic policy and legislation, economic incentives, and levels of public acceptance, and these factors are unlikely to be major determinants of agricultural carbon emissions. Even if there are time-invariant factors that could affect both the timing of adoption and carbon emissions, they should have been accounted for by the country-fixed effects. Appendix Table A4 provides further support for the exogeneity of the timing of GM crop adoption by showing that it is uncorrelated with major determinants of agricultural carbon emissions.

To evaluate the average effect of GM crop adoption, we also estimate the following staggered DID model:

$$lny_{it} = \alpha + \beta_1 Treat_i \times Post_t + \mu_i + \lambda_t + X_{it}\theta + \varepsilon_{it} \tag{16}$$

where the dummy variable $Post_t$ equals 1 for years after the first GM crop adoption and equals 0 otherwise, and the dummy variable $Treat_i$ equals 1 for countries that adopted any of the four GM crops and 0 otherwise. All other model settings are the same as those in the event study model.

[7]The climatic measures are annual mean temperature, annual total precipitation, diurnal temperature range, mean cloud cover, ground frost frequency, potential evapotranspiration, vapor pressure, and number of rain days.

[8]We adopt the standard region classification of East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa.

4.3 Crop-level regression models

We use the following crop-level event-study regression model for robustness checks and mechanism analyses:

$$y_{ict} = \alpha + \sum_{j=2}^{J} \beta_j (Lag\, j)_{ict} + \sum_{k=0}^{K} \gamma_k (Lead\, k)_{ict} + \sigma_{it} + \omega_{ct} + \pi_{ic} + \varepsilon_{ict} \tag{17}$$

where y_{ict} is the outcome variable of interest for crop c in country i and year t. We do not apply log transformation to the outcome variable because the crop-level data contains many zeros; many countries do not cultivate all of the four crops. As an instead, we follow the literature (Cohn *et al.*, 2022; Chen & Roth, 2024) and adopt Poisson regression with a quasi-maximum likelihood method to estimate the effect at the crop level. σ_{it}, ω_{ct}, and π_{ic} are country-by-year fixed effects, crop-by-year fixed effects, and country-by-crop fixed effects, respectively. Therefore, the identification depends mainly on within-country variation across crops and over time, further reducing concerns of omitted variables. The lags and leads are defined at the crop level; the first harvested year of the GM variety of crop c in country i is defined as the event time. The error term is clustered at the country-crop level.

We estimate the following crop-level staggered DID model to capture the average effect:

$$y_{ict} = \alpha + \beta_1 Treat_{ic} \times Post_{tc} + \sigma_{it} + \omega_{ct} + \pi_{ic} + \varepsilon_{it} \tag{18}$$

where the dummy variable $Treat_{ic}$ equals one if crop c in country i is one of the four major GM crops, and the dummy variable $Post_{tc}$ equals one if year t is after the adoption of the GM variety of crop c in the country. All other variables are defined the same as in model (17).

Non-GM crops are used as the pure control group in the estimation. To enhance comparability, we limit the pure control crops to the FAO classification of cereals, pulses, oil crops, and fiber crops that belong to the same crop types as the four GM crops. We exclude fruits, nuts, vegetables, and tuber and root crops because they are biologically different from the four GM crops and differ in production methods. For robustness checks, we further limit the pure control crops to 15 crops that are biologically most similar to the four GM crops: rice, wheat, barley, sorghum, lentils, chickpeas, millet, groundnuts, cowpeas, pigeon peas, melonseed, bambara beans, jute, kenaf, and ramie.

5 Main Results

5.1 Total carbon emissions

Figure 7 presents the dynamic effects of GM crop adoption on carbon emissions, estimated based on the Event-Study model (15). We estimate both the effects on crop carbon emissions and total agricultural carbon emissions. As detailed in subsection 3.1, the adoption of GM crops could affect the carbon emission from non-GM crops and non-crop agricultural production. As such, our baseline estimation focuses on the entire agricultural sector and all crops, rather than only the GM crops. The estimates suggest that countries exhibited no differing trends in carbon emissions before GM crop adoption, consistent with the parallel trends hypothesis. The estimates also suggest that GM crops significantly increased carbon emissions over time. The estimated effect on agricultural carbon emissions is comparable to that on crop carbon emissions, suggesting a substantial effect on the carbon emission of non-crop productions, which will be verified later.[9]

[9]Figure 7 also shows that the carbon-emission effect peaked approximately five years after the adoption of GM crops, consistent with the observation in Appendix Figure A1 that once a country adopts GM crops, the adoption rate of the GM crops tends to peak in approximately five years.

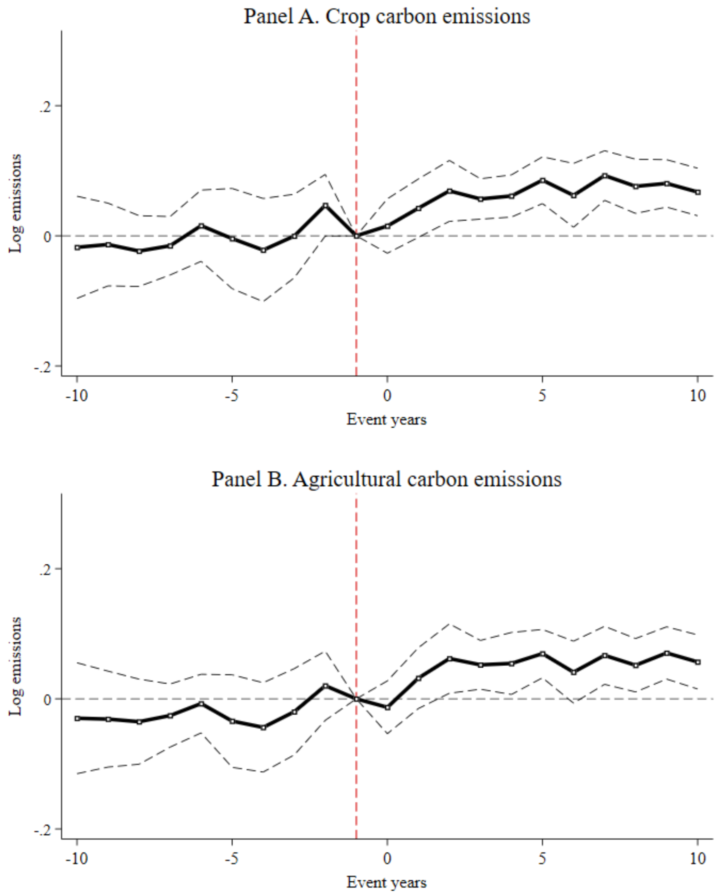

Figure 7: Dynamic effects of GM crop adoption on agricultural carbon emissions

Notes: This figure presents the event-study estimates based on model (15) and the corresponding 95% confidence intervals. The dependent variables in Panels A and B are the country-level total carbon emissions from the cropping sector and the entire agricultural sector, respectively. The dashed vertical line indicates the year prior to GM crop adoption. The confidence intervals are computed based on standard errors clustered at the region-year level.

We provide several robustness checks for the baseline event-study estimates. Appendix Figure A5 addresses the potential concern of treatment effect heterogeneity by adopting the interaction-weighted estimators of Sun & Abraham (2021) and the interpolated estimators of Borusyak *et al.* (2024). The resulting estimates are comparable to the baseline estimates. Appendix Figure A6 utilizes the approval time instead of the adoption time of GM crops as the event time and finds similar estimates. Finally, we exclude rapeseed, the GM crops that has been adopted only in three countries, from the estimation and find the same estimates.[10]

Table 1 reports the DID estimates based on model (16). Column 1a shows that GM crop adoption increased crop carbon emissions by 8.1%. The estimate remains robust

[10]Excluding rapeseed results in exactly the same estimates because rapeseed is not the first GM crop adopted in these three countries; our event study utilizes the adoption year of the first GM crops in a country as the event time.

when a set of climatic control variables is included (column 1b) to address the concern that the finding could be confounded by the reverse effect of climate change (Stocker *et al.*, 2013). The estimate is also robust to excluding data before 1990 (column 1c) to address the potential confounding effect of earlier policies. Appendix Tables A5 and A8 provide additional robustness checks to show that the result is not sensitive to using the approval time of GM crops as the event time, using the adoption rate of GM crops as the key explanatory variable, adopting a Poisson regression, and excluding the top 3 GM-crop production countries from the sample.

Table 1: Effects of GM crop adoption on agricultural carbon emissions

	Crop carbon emissions			Agricultural carbon emissions		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
$Treat_i \times Post_t$	0.081***	0.071***	0.078***	0.081***	0.074***	0.090***
	[0.025]	[0.022]	[0.025]	[0.027]	[0.025]	[0.026]
Control variables	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Drop years before 1990	No	No	Yes	No	No	Yes
Observations	4,364	4,241	3,741	4,364	4,241	3,741

Notes: This table presents the effect of GM crop adoption on total agricultural carbon emissions, estimated based on model (16). Columns 1a–1c present the effect on crop carbon emissions, and Columns 2a–2c present the effect on agricultural carbon emissions. Columns 1a and 2a present the baseline estimate, columns 1b and 2b additionally control for a set of climatic measures (see Footnote 7), and columns 1c and 2c exclude data before 1990. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Columns 2a–2c present the estimated effect on agricultural carbon emissions. One would expect to see a smaller effect on agricultural carbon emissions than on crop carbon emissions if GM crops only affect the cropping sector. However, the estimated effect on agricultural carbon emissions is close to that on crop carbon emissions, suggesting that GM crops also significantly increased the carbon emissions of non-crop agricultural production. Appendix Table A6 supports this observation by showing that GM crop adoption increased the carbon emissions from livestock production by 12.0%. The corresponding event study (Appendix Figure A7) confirms that the estimated effect on emissions from livestock production is not driven by preexisting trends. This finding is consistent with the fact that the four GM crops, along with their stalks, serve as major inputs in livestock production (see Footnote 3 for details).

5.2 Emission intensity

We then estimate the impact on crop carbon-emission intensity. We adopt two intensity measures: emissions per area and emissions per yield of crop. As it is difficult to measure the emission intensity of the entire agricultural sector, our main analysis focuses only on crop carbon-emission intensities.[11] Examining the effect on crop emission intensity enables us to show that GM crops affect total carbon emissions not only through increasing total crop output. If total crop carbon emission is proportional to total crop output, we should find no significant effect of GM crops on crop carbon emissions per area or per yield.

Figure 8 presents the event-study estimates based on model (15). Panel A presents the effect on per area carbon emissions, while Panel B presents the effect on per yield carbon emissions. The estimates support the parallel trends assumption and suggest a significantly positive and increasing effect on carbon emissions per area and per yield over time. Appendix Figure A8 presents similar parallel trends and dynamic effects when using the approval time of GM crops in each country, instead of the adoption time as the event time in the event study.

[11] Appendix Figure A9 adopts the intensity measure of carbon emissions per value of agricultural output and found a comparable result.

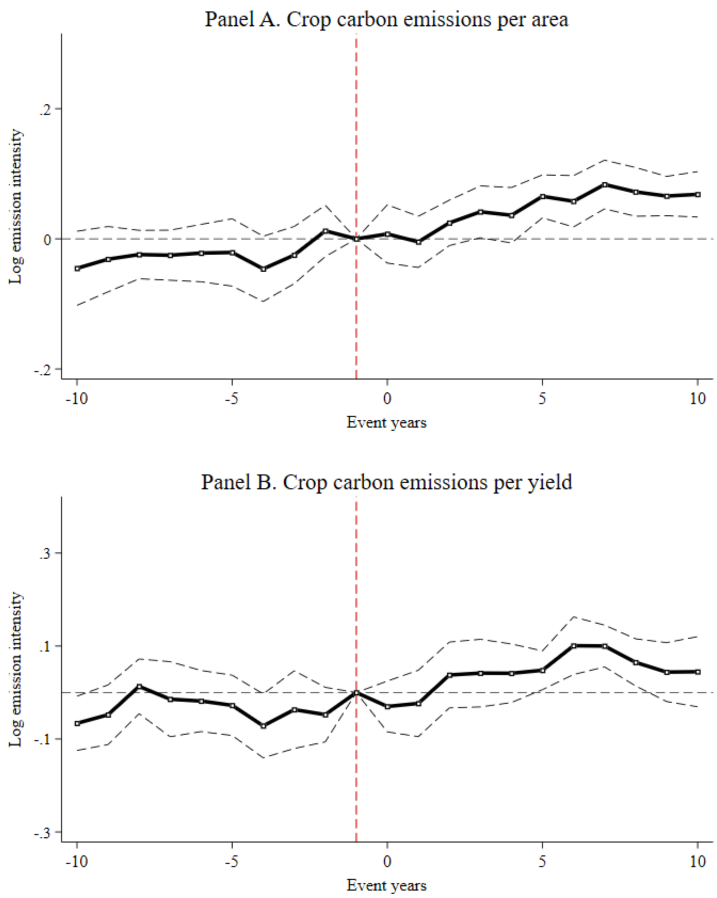

Figure 8: Dynamic effects of GM crop adoption on crop carbon-emission intensities
Notes: This figure presents the event-study estimates based on model (15) and the corresponding 95% confidence intervals. The dependent variables in Panels A and B are the country-level crop carbon emissions per area and per yield, respectively. The dashed vertical line indicates the year before GM crop adoption. The confidence intervals are computed based on standard errors that are clustered at the region-year level.

Table 2 reports the DID estimates based on model (16). Column 1a shows that GM crops increased crop carbon emissions per area by 10.8%. The estimate is robust to including a set of climatic control variables (column 1b) and excluding data before 1990 (column 1c). Columns 2a–2c show similar results for crop carbon emissions per yield. Additional robustness checks presented in Appendix Tables A7 and A8 find comparable results when using the approval time of GM crops as the event time, using the adoption rate of GM crops as the key explanatory variable, and adopting a Poisson regression to estimate the effect, and excluding the top 3 GM-crop production countries from the sample. These findings suggest that the estimated effect on total carbon emissions is not solely driven by a proportional increase in total crop output.

Table 2: Effects on crop carbon-emission intensity

	Carbon emissions per area kg/ha			Carbon emissions per yield kg/ton		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
$Treat_i \times Post_t$	0.108***	0.091***	0.087***	0.102***	0.094***	0.101***
	[0.016]	[0.014]	[0.015]	[0.017]	[0.017]	[0.018]
Control variables	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes	Yes	Yes
Drop years before 1990	No	No	Yes	No	No	Yes
Observations	4,364	4,241	3,741	4,364	4,241	3,741

Notes: This table presents the effect of GM crop adoption on crop carbon-emission intensities, estimated based on model (16). Columns 1a–1c present the effect on emissions per area, while columns 2a–2c present the effect on emissions per yield. Columns 1a and 2a present the baseline estimate, columns 1b and 2b additionally control for a set of climatic measures, and columns 1c and 2c exclude data before 1990. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.3 Crop-level estimates

To further verify the impact of GM crops on carbon emissions, we present crop-level estimates for maize and soybean, the two major GM crops with carbon emission data. The estimation is based on a comparison of carbon emissions from these two crops with emissions from non-GM crops with carbon emissions data (barley, millet, oats, potatoes, rice, rye, sorghum, sugar cane, and wheat). Table 3 presents the crop-level DID estimates based on model (18). We find that the adoption of the GM varieties for maize and soybean increased their total carbon emissions by 14.4% (column 1a), emissions per area by 5.7% (column 2a), and emissions per yield by 10.5% (column 3a). Columns 1b, 2b, and 3b present the robustness checks that exclude the less comparable non-GM crops from the control group of the estimation (i.e., potatoes, rice, and sugar cane). The resulting estimates are similar. The effects on total carbon emissions and carbon emissions per yield are comparable to those estimated for the whole cropping sector (Tables 1 and 2). The estimated effect on carbon emissions per area is only about half of that estimated for the whole cropping sector. This finding is consistent with the fact that the adoption of the GM varieties increased the multiple cropping of these two major GM crops (see Table 6).[12]

[12] The crop area in this study refers to crop harvested area. An increase in multiple cropping mean an increase in the harvested area for given farmland.

Table 3: Effects on the carbon emissions from maize and soybean production

	Total emissions		Emissions per area		Emissions per yield	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
$Treat_{ic} \times Post_{ct}$	0.144** [0.062]	0.153** [0.062]	0.057*** [0.012]	0.057*** [0.012]	0.105*** [0.031]	0.105*** [0.031]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Country-crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Non-GM crops	All	Comparable	All	Comparable	All	Comparable
Observations	40,261	32,118	40,261	32,118	40,260	32,117

Notes: This table presents the effects of the adoption of GM varieties on total carbon emissions (columns 1a–1b), emissions per area (columns 2a–2b), and emissions per yield (columns 3a–3b) for maize and soybean, estimated based on Model (18) using Poisson regression. The control group in columns 1a, 2a, and 3a includes all non-GM crops with carbon emissions data (barley, millet, oats, potatoes, rice, rye, sorghum, sugar cane, and wheat), while the control group in 1b, 2b, and 3b excludes the less comparable non-GM crops (i.e., potatoes, rice, and sugar cane). Standard errors reported in square brackets are clustered at the country-crop level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.4 Heterogeneity

We examine the heterogeneity in the effect of GM crops on crop carbon emissions across countries with different levels of crop output per capita, farmland per capita, GDP per capita, annual mean temperature, and annual total precipitation. We construct a dummy variable for each of these moderating variables. The dummy variable equals one for countries where the 1995 value of the moderating variable is above the median, and zero otherwise. We then interact the dummy variable with the DID component of model (16) to examine the effect heterogeneity:

$$lny_{it} = \alpha + \beta_1 Treat_i \times Post_t + \beta_2 Treat_i \times Post_t \times Dummy_i + \mu_i + \lambda_t + X_{it}\theta + \varepsilon_{it} \quad (19)$$

We plot the estimates of β_1 (Low) and $\beta_1 + \beta_2$ (High) in Figure 9. The corresponding point estimates are presented in Appendix Tables A9 and A10.

We find no significant heterogeneity in the effect on total crop carbon emissions (Panel A) with respect to each of the five moderating variables, although the effects are larger (but not statistically significant) for countries with farmland per capita and GDP per capita below the median. However, we find significantly larger effects on carbon emissions per yield (Panel B) for countries with farmland per capita and GDP per capita below the median. This finding is consistent with the theoretical prediction that the expansion of the GM crop production to low-quality marginal lands is a key reason for the increase in carbon emissions per yield; countries with lower farmland per capita and lower GDP per capita are more likely to reclaim low-quality marginal lands when facing the potential gains from GM crop production.

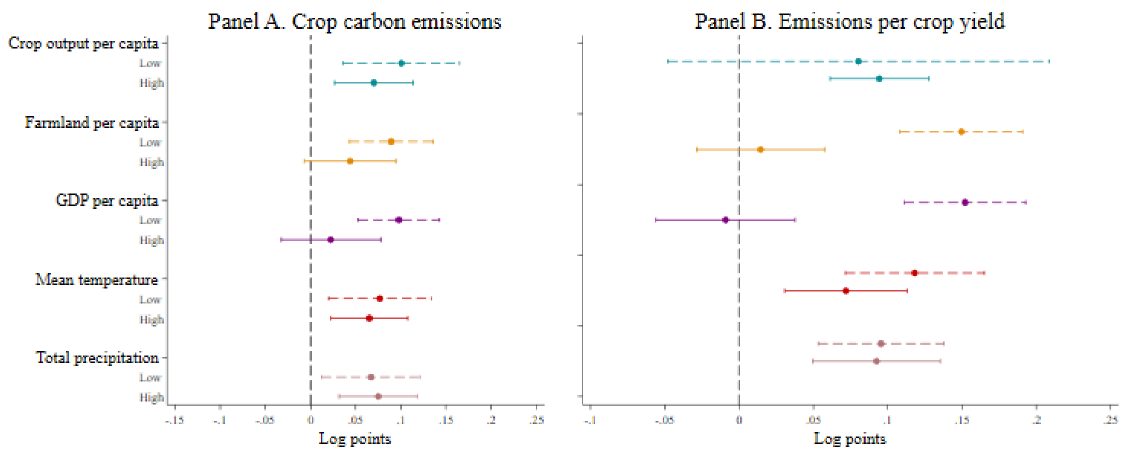

Figure 9: Heterogeneity of the effect on total carbon emissions (Panel A) and carbon emissions per yield (Panel B)

Notes: This figure presents the heterogeneity in the effect of GM crops on carbon emissions with respect to crop output per capita, farmland per capita, GDP per capita, annual mean temperature, and annual total precipitation. All moderators are dummy variables that equal one for countries with the 1995 value of the moderator above the median. The 95% confidence intervals (horizontal lines) are calculated using standard errors clustered at the region-year level.

6 Mechanisms

This section examines the channels through which GM crops affect agricultural carbon emissions. As presented in Figure 5, there are two major direct effect channels (i.e., production inputs and land use changes) and two major indirect effect channels (i.e, livestock production and agricultural trade) through which GM crops affect carbon emissions.Before examining these effect channels, we verify that GM crops increased crop yield and harvested area, which are preconditions for GM crops to increase carbon emissions.

6.1 Effect on the yield and harvested area of GM crops

Table 4 presents the DID estimates of the effects on the yield and harvested area of the four GM crops. The estimation is based on the crop-level regression model (18) that compares the GM crops with non-GM crops that are biologically similar to these four crops. The corresponding event-study estimates for all four crops together and for each crop individually are presented in Appendix Figures A10 and A11.

Columns 1 and 3 of Table 4 show that the adoption of GM varieties increased the yield and harvested area of the four GM crops by 13.8% and 15.0%, respectively.[13] These effects are close to the estimated effect on carbon emissions from the GM crops (Table 3). Columns 2 and 4 report the annual effect of GM crops, estimated based on a modified version of model (18) that interacts the DID dummy with the number of years after the adoption. We find an annual effect of 2.0% and 2.7% on yield and harvested area, respectively, which is close to the estimates in the literature (Scheitrum *et al.*, 2020).

Table 4: Effect of the adoption of GM varieties on the yield and harvested area of the four GM crops

	(1)	(2)	(3)	(4)
	Yield		Area harvest	
$Treat_{ic} \times Post_{ct}$	0.138***		0.150**	
	[0.036]		[0.068]	
$Treat_{ic} \times Posttime_{ct}$		0.020***		0.027***
		[0.005]		[0.009]
Country-crop FE	Yes	Yes	Yes	Yes
Year-country FE	Yes	Yes	Yes	Yes
Year-crop FE	Yes	Yes	Yes	Yes
Observations	35,526	35,526	36,958	36,958

Notes: This table presents the effect of the adoption of GM varieties on the yield (columns 1 and 2) and harvested area (columns 3 and 4) of the four GM crops, estimated based on Model (18). While columns 1 and 3 present the average effect, columns 2 and 4 present the annual average effect. Standard errors reported in square brackets are clustered at the country-crop level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

6.2 Effect on production inputs

Table 5 shows that GM crop adoption increased per area fertilizer use (column 1) and energy use (column 3) by 23.3% and 8.0%, respectively, but had no significant effect on pesticide use (column 2) and irrigation area (column 4). These effects are estimated based on regression model (16), which uses country-level per harvested

[13]Some of the previous studies do not find a significantly positive effect of GM varieties on the harvested area (Sexton & Zilberman, 2011; Barrows *et al.*, 2014, e.g.). A potential explanation is that these studies do not exclude crops that are not biologically comparable to GM crops from the control group in the estimation. We have also tried to include all non-GM crops in the control group and found a statistically insignificant effect on the harvested area (not reported).

area inputs of crop production as the dependent variables; crop-level input data are generally unavailable. Since fertilizer and energy are major sources of agricultural carbon emissions, these estimates explain why GM crops substantially increased the intensity of carbon emissions.[14]

Table 5: Effect of GM crop adoption on per area inputs of crop production

	(1) Log fertilizer per area	(2) Log pesticide per area	(3) Log energy per area	(4) Log total irrigation area
$Treat_i \times Post_t$	0.233***	0.065	0.080*	-0.019
	[0.042]	[0.040]	[0.042]	0.013
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	3,865	3,620	3,737	4,108

Notes: This table presents the effects of GM crop adoption on per area inputs in crop production, estimated based on a modified version of the country-level DID Model (16) that uses each input as the dependent variable. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

6.3 Effects on land uses

Changes in agricultural land use types. We estimate the effect of GM crops on country-level agricultural land use based on model (16). As presented in Table 6, we find that GM crops increased the total farmland area by 3.5% (column 1) and increased the crop harvested area by 6.8%. The larger effect on crop harvested area than on farmland area suggests a positive effect on multiple cropping, which is another reason for the increased inputs. We also find that GM crops reduced tree cover by 0.9% (column 3) and forest area by 0.3% (column 4), although the later estimate is not statistically significant at the conventional level. Tree cover area includes fragmented areas of tree coverage adjacent to contiguous forested regions. As tree cover is a net carbon sink (Vestin, 2024), shifting land use from tree cover to crop production necessarily increases agricultural carbon emissions.

[14]The insignificant effect on pesticide use is likely due to the offsetting effects of the pesticide-saving nature of major GM crops and the expansion to marginal lands that requires more pesticides. The insignificant effect on irrigation areas is potentially because irrigation is mainly determined by water endowments.

Table 6: Effect of GM crops on agricultural land use

	(1) Log farmland area	(2) Log crop harvested area	(3) Log tree cover area	(4) Log forest area
$Treat_i \times Post_t$	0.035***	0.068***	-0.009***	-0.003
	[0.012]	[0.021]	[0.004]	[0.008]
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	4,241	4,241	3,532	3,741

Notes: This table presents the effect of GM crop adoption on country-level agricultural land use, estimated based on a version of the DID model (16) that uses log area of different types of agricultural land as the dependent variables. The tree cover area in column 3 includes fragmented areas of tree coverage adjacent to contiguous forested regions. The sample sizes for tree cover and forest area are smaller because data for these two variables are only available from 1991 and 1993 onward, respectively. The reported standard errors are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Crowding-out non-GM crops. In addition to affecting land use types, GM crops may have also crowded out non-GM crops. We estimate the crowding-out effect based on a version of the crop-level DID model (18) that uses the area of non-GM crops as the dependent variable. Specifically, we estimate the effect of GM crop adoption on the harvested area of non-GM crops of the same types as the four GM crops. As presented in Appendix Table A11, the adoption of GM crops reduced the area of the same types of non-GM crops by 4.1% (column 1). The effect is even larger (7.6%) when focusing on the 15 most botanically similar crops (column 2). Based on the assumption that crops are cultivated in lands most suitable for them before GM crop adoption, the crowding out of non-GM crops implies the use of less suitable land for GM crop production. This could increase production inputs and thus carbon emissions.

Utilizing marginal lands. The high profit of GM crops may have led to the utilization of marginal land with lower quality. This could increase carbon emissions as marginal lands generally require more fertilizer and energy inputs. We do not have crop-level land quality data that can be used for rigorous analysis. The best available data are the crop-level land quality measures from FAO's GAEZ database (FAO, 2021), which are only available for 2000 and 2010.[15] We have presented in Figure 3 the expansion of the cultivated area of major GM crops from 2000 to 2010 and the decline in land quality for these crops. Appendix Figure A12 further supports this by comparing land quality changes for each crop from 2000 to 2010 between countries that adopted

[15] As detailed in subsection 2.3, the GAEZ data measures land quality by crop-specific attainable yield, calculated by combining climate, soil, and terrain factors of the land used for each crop. Therefore, the changes in land quality over time arise solely from changes in the cultivated area.

the GM varieties before 2010 and countries that did not. We find a significant decline in land quality for maize and soybean in GM countries but not in non-GM countries.

6.4 Effects on livestock production and agricultural trade

This subsection provides suggestive evidence on the indirect effect of GM crops on carbon emissions through livestock production and agricultural trade. First, we estimate the effect of GM crop adoption on the production and export of crops and livestock. Then, we combine these estimates with the carbon intensity of each product in GM and non-GM countries to infer the effect of agricultural trade.

Columns 1 and 2 of Table 7 present that the adoption of GM crops increased major crop production and export by 5.6% and 19.6%, respectively. These effects are estimated based on modified versions of model (16) that use major crop production and export as the dependent variables.[16] When combining these effect estimates with country-average production and export (also reported in the table), we calculate that GM crops increased country-average crop production and export by 839 and 332 kilotonne, respectively. Therefore, a large share (71.6%) of the increased crop output was used for domestic consumption instead of export.

Table 7: Effect of GM crops on agricultural production and export

	Major crops		Livestock	
	(1) Production	(2) Export	(3) Production	(4) Export
$Treat_i \times Post_t$	0.056**	0.196***	0.296***	0.622***
	[0.025]	[0.067]	[0.033]	[0.080]
Dependent variable mean (kt)	14988	1696	1348	186
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes
Observations	4,113	3,884	3,918	3,310

Notes: This table presents the effect of GM crop adoption on the production and export of major crops (columns 1–2) and livestock (columns 3–4), estimated based on model (16). The major crops are maize, soybean, wheat, rice, potatoes, barley, millet, oats, rye, and sorghum. The livestock refers to meat, eggs, and dairy; these products are combined after being converted to protein equivalent quantity. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

As major GM crops (i.e., soybean and maize) are typically used for livestock

[16]The major crops examined are maize, soybean, wheat, rice, potato, barley, millet, oats, rye, and sorghum. We focus on major crops instead of only the GM crops because GM crops could affect the production and export of non-GM crops.

production, we also investigate the effect of GM crops on the production and export of livestock. As presented in columns 3 and 4 of Table 7, we find that GM crop adoption increased the production and export of livestock by 29.6% and 62.2%, respectively. The livestock refers to meat, egg, and dairy; these products are combined after transformed to protein equivalent quantity. Given that using crops to produce livestock generates additional carbon emission (Herrero *et al.*, 2013; Havlík *et al.*, 2013), the substantial increase in domestic livestock production suggests that livestock production is an important channel through which GM crops to increase agricultural carbon emissions.

The effect of agricultural trade on global carbon emissions depends on the relative carbon-emission intensities of crop and livestock production in GM and non-GM countries. Panel A of Figure 10 shows that the carbon-emission intensity is much higher in non-GM countries than in GM countries for maize and soybean (two GM crops with carbon emission data). We calculate the average carbon-emission intensity as the weighted average emissions per ton of yield, using 1996 national total output of the product as the weights. As such, exporting GM crops to non-GM countries could reduce global carbon emissions. Panel B of the figure shows that the livestock carbon-emission intensity is slightly lower in non-GM countries than in GM countries.[17] Therefore, exporting livestock to non-GM countries may not reduce global carbon emissions.

[17]Livestock here includes meat, eggs, and dairy, aggregated in protein-equivalent terms. Livestock carbon emissions mainly come from feed production, methane from digestion, manure, and land use. Beef has the highest footprint, at 20-30 tons of CO_2 per ton, due to high methane emissions and resource needs. Pork and poultry are lower, at 5-7 and 4-5 tons per ton, respectively, due to better feed efficiency and less methane.

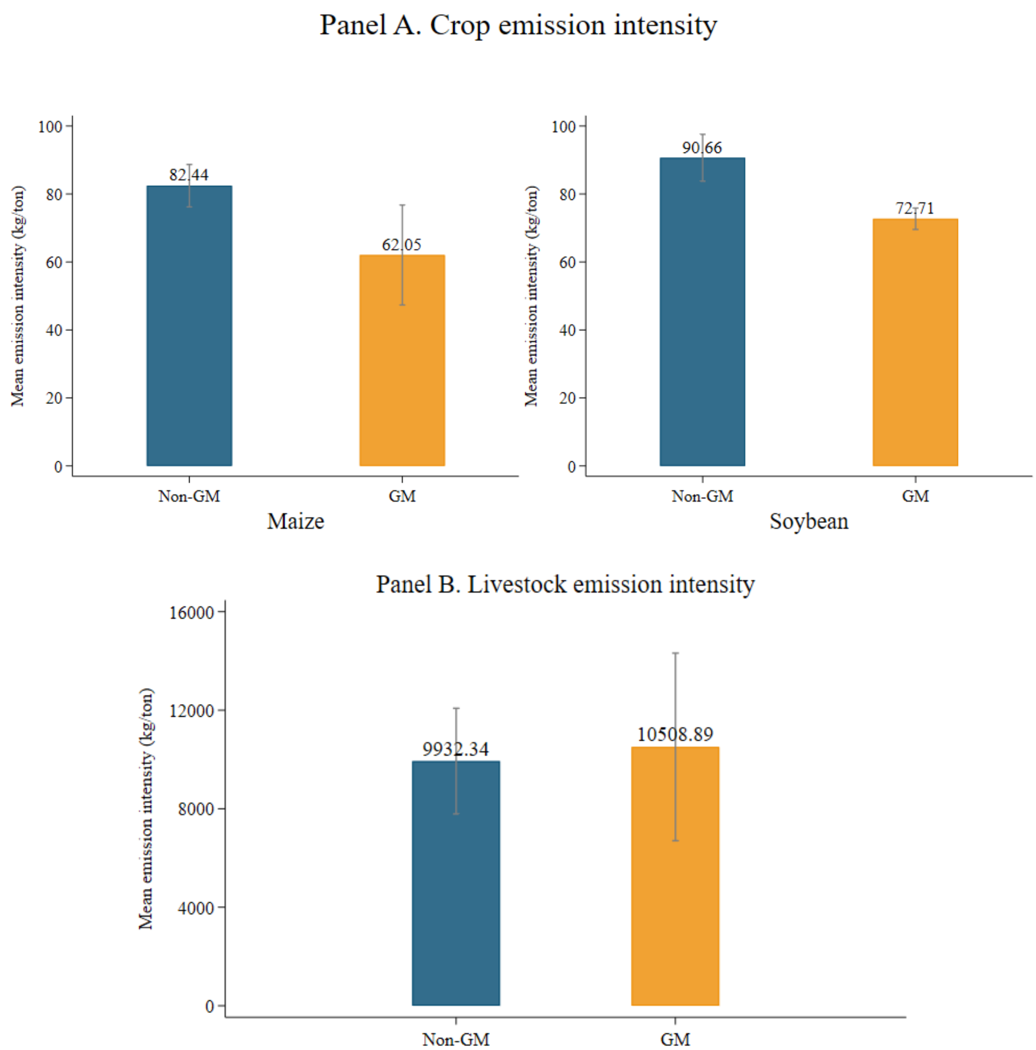

Figure 10: Carbon-emission intensity in GM and non-GM countries

Notes: This figure presents the weighted average carbon emissions per yield for crops (Panel A) and livestock (Panel B) in GM and non-GM countries. We use the 1995 country-level total output of each product as the weights. Livestock refers to meat, eggs, and dairy; these products are combined after being converted to protein-equivalent quantities.

In sum, encouraging the export of GM crops instead of the derived livestock products may help mitigate the impact of GM crops on global carbon emissions. While we observe that crop exports could partly offset the impact of GM crops on global carbon emissions, less than one-third of the additional crop output resulting from GM crop adoption is directly used for export. Most of the additional crop output are used for domestic consumption, especially for livestock production. The domestic production and export of livestock further increase global carbon emissions.

7 Concluding Remarks

As agrifood systems contribute 30% of global total anthropogenic carbon emissions, exploring ways to reduce agricultural carbon emissions is of great significance for mitigating climate change. GM crops, initially developed and adopted to boost crop resilience and agricultural productivity, are believed to mitigate agricultural carbon emissions by reducing input use and conserving land. Over the past two decades, the harvested area of GM crops has been increasing at an annual rate of 8.6%, accounting for more than 23.7% of the harvested area of all field crops worldwide by 2023. However, we did not observe a decline in agricultural carbon emissions following the adoption of GM crops. Instead, the opposite trend was observed.

We develop a theoretical model to show that if the adoption of GM crops leads farmers to extend cultivation to low-quality marginal lands, both total carbon emissions and carbon-emission intensity will increase. This prediction is consistent with our empirical findings that the adoption of the GM varieties increased the yield and harvested area of the major GM crops, increased total crop areas, increased multiple cropping, crowded out non-GM crops, reduced tree cover, increased per area input of fertilizer and energy, and reduced the average quality of cultivated cropland.

The findings of this study suggest that agricultural technological progress does not necessarily reduce carbon emissions, even if the technology increases the efficiency of high-emission input use. Instead, consistent with the Jevons paradox, input saving technology such as GM crops increases agricultural carbon emissions. Policies that limit GM crops to lands most suitable for them could mitigate their effect on agricultural carbon emissions. Policies encouraging the export of GM crops to countries with higher crop carbon-emission intensities could also help mitigate the impact on global carbon emissions.

We conclude by highlighting that our study does not assess the effect of GM crops on welfare. Existing studies generally find that GM crop adoption increased crop yield (Villoria, 2019; Hansen & Wingender, 2023), implying a welfare gain through alleviating global food supply pressures and increasing the income of farmers. Many studies also suggest a welfare-improving effect of GM crops through reducing the environmental and health risks of chemical pollution (Carpenter, 2010; Ahmed *et al.*, 2021). Our study does not evaluate the relative magnitudes of welfare gain from these channels and welfare losses from carbon emissions.

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A Appendix for Online Publication

A.1 Figure

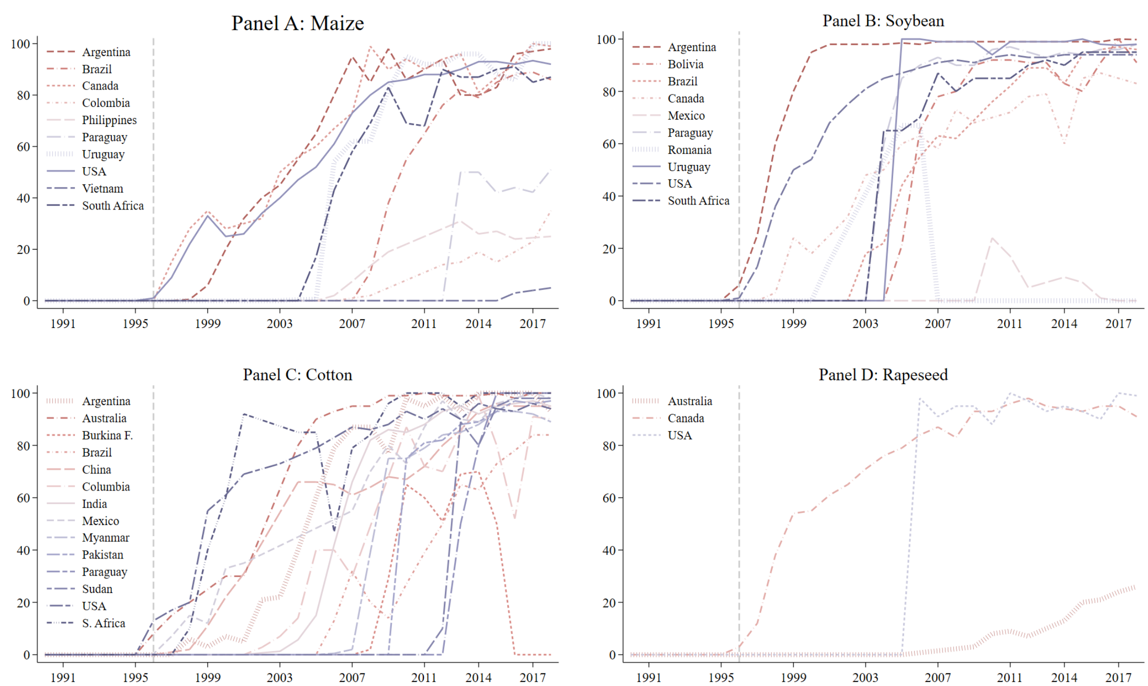

Figure A1: Adoption rate of GM crops in each country

Notes: The data are derived from Hansen & Wingender (2023). The first harvest year of GM crops could be earlier than the approved commercialization year in some countries where there is no legislation or existing legislation has not been enforced.

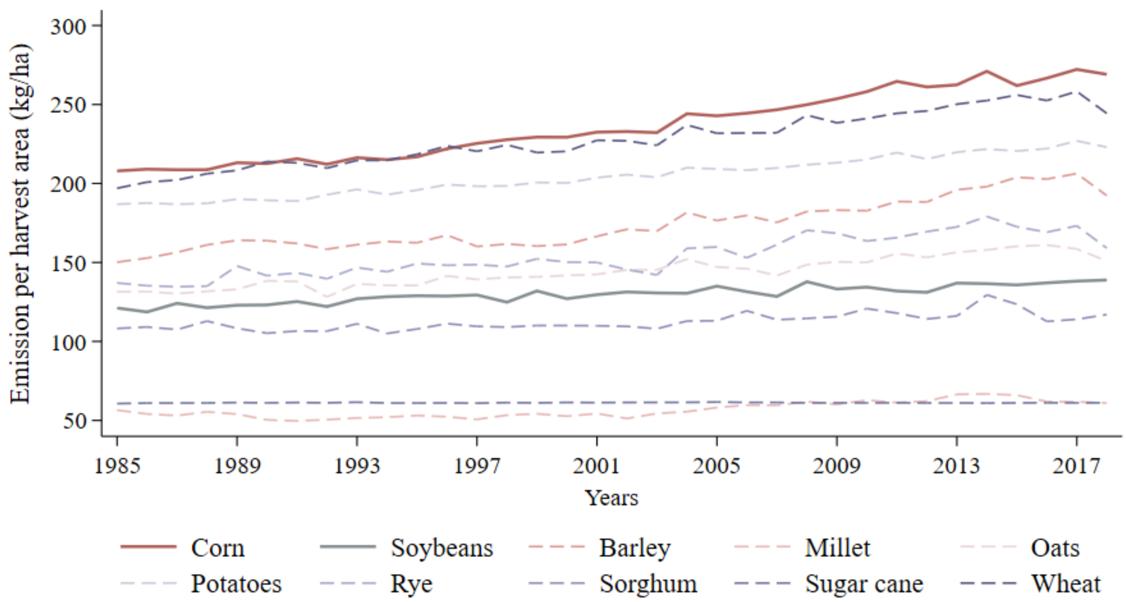

Figure A2: Crop-level trends of carbon emissions per area

Notes: The figure presents the global-average carbon emissions per area for each of the major crops.

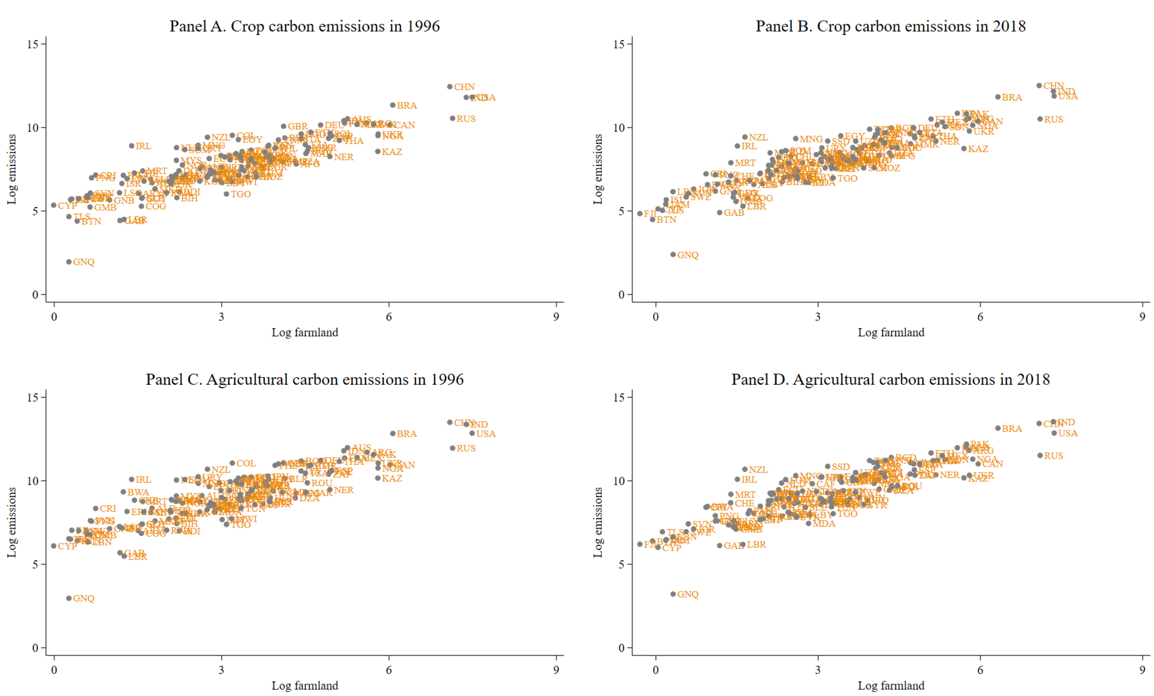

Figure A3: Log agricultural carbon emissions in each country

Notes: The figure presents the association between log agricultural carbon emissions and log farmland area across countries in 1996 and 2018, respectively.

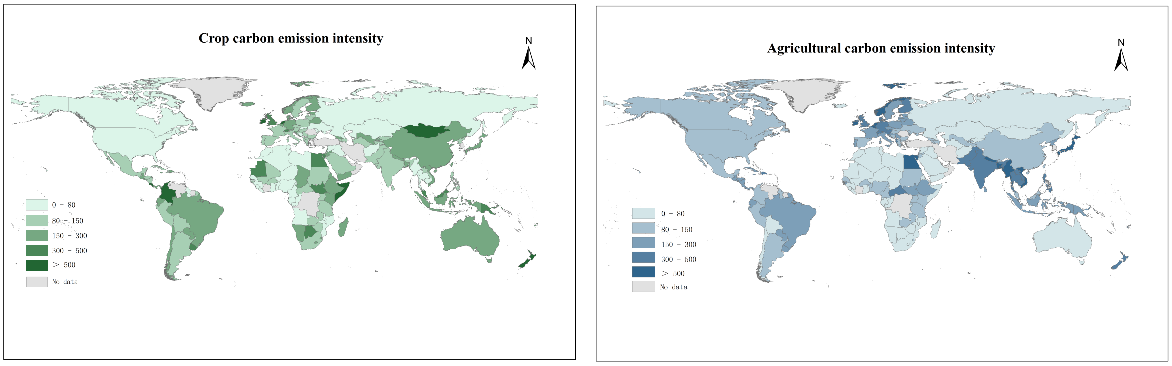

Figure A4: Carbon emissions per area of agricultural production

Notes: The figure presents the carbon emissions per area (kt/km^2) for crop production (left) and agricultural production (right) in each country, calculated as the average from 1985 to 2018.

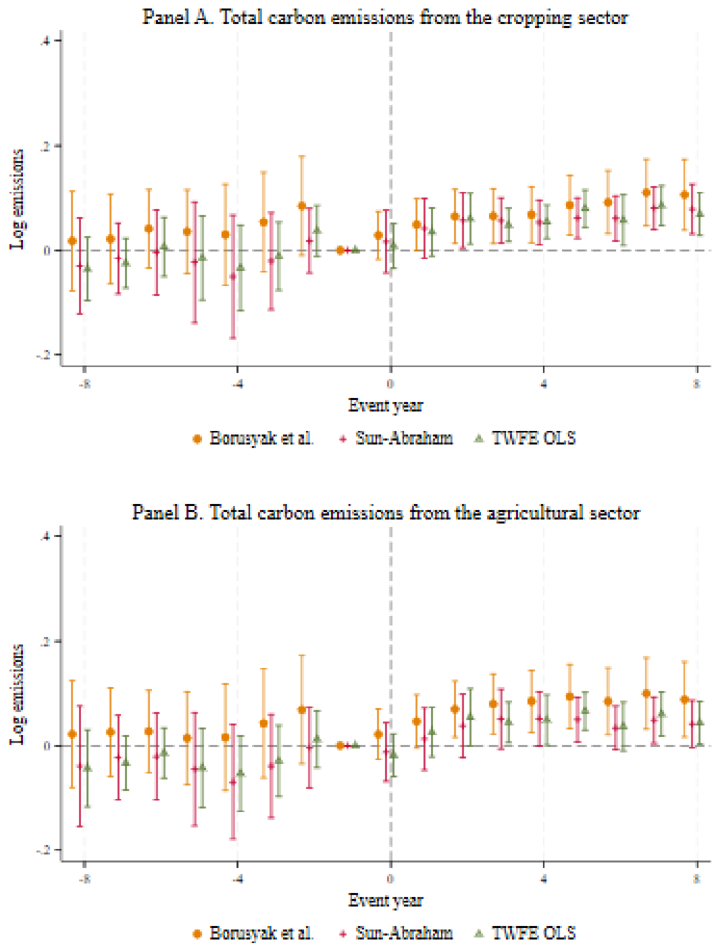

Figure A5: Robust to treatment effect heterogeneity

Notes: This figure addresses the potential concerns regarding treatment effect heterogeneity of the baseline event-study estimates presented in Figure 7 by adopting the interaction-weighted estimators of Sun & Abraham (2021) and the interpolated estimators of Borusyak *et al.* (2024). The dependent variables in Panels A and B are the country-level total carbon emissions from the cropping sector and the entire agricultural sector, respectively. The dashed vertical line indicates the year prior to GM crop adoption. The confidence intervals are computed based on standard errors that are clustered at the region-year level.

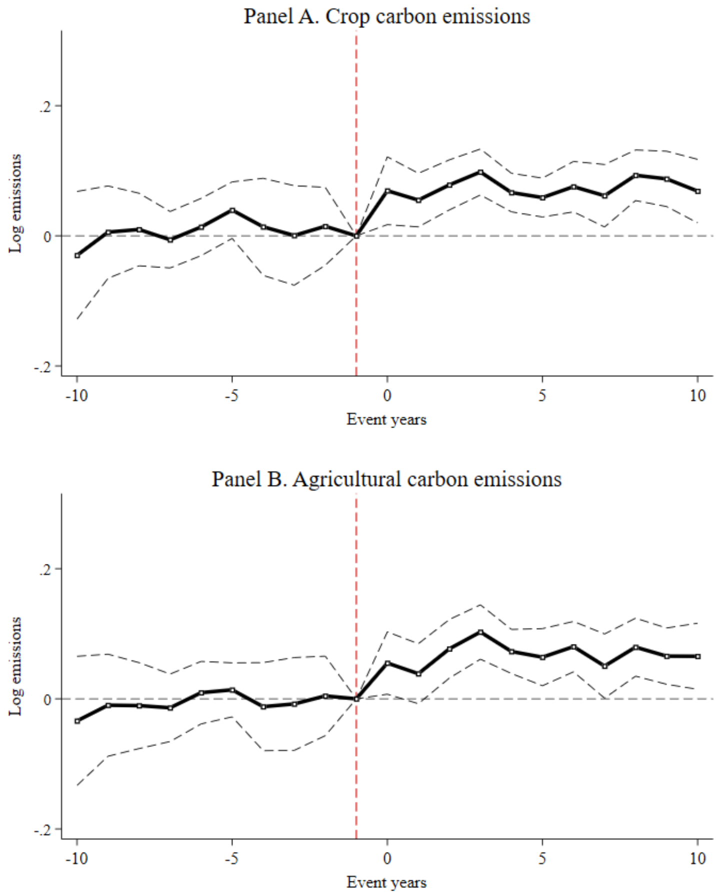

Figure A6: Robust to using the approval time as the event time

Notes: As a robustness check for the baseline event-study estimates in Figure 7, this figure substitutes the approval time for the adoption time of GM crops as the event time. The dependent variables in Panels A and B are the country-level total carbon emissions from the cropping sector and the entire agricultural sector, respectively. The dashed vertical line indicates the year before GM crop adoption. The confidence intervals are computed based on standard errors that are clustered at the region-year level.

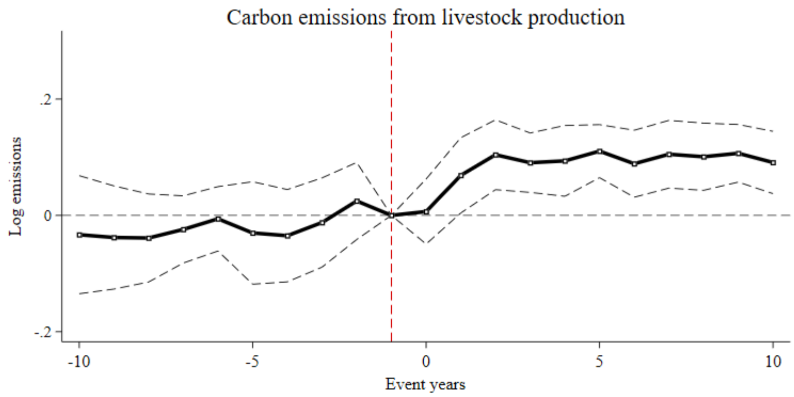

Figure A7: Dynamic effects of GM crops on livestock carbon emissions

Notes: This figure presents the effect of GM crop adoption on carbon emissions from livestock production, estimated based on model (15). The confidence intervals are computed based on standard errors that are clustered at the region-year level.

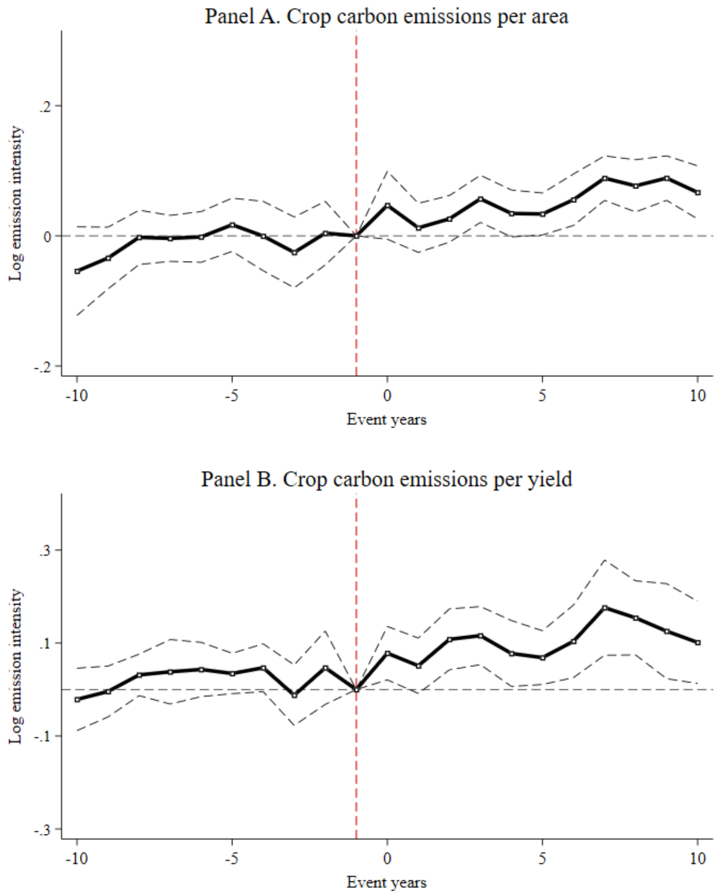

Figure A8: Dynamic effects of GM crop adoption on crop carbon-emission intensities (approval time)

Notes: This figure provides a robustness check for the event-study estimates shown in Figure 8, using the approval time of GM crops in each country instead of the adoption time as the event time. The dependent variables in Panels A and B are the country-level crop carbon emissions per area and per yield, respectively. The dashed vertical line indicates the year before GM crop adoption. The confidence intervals are computed based on standard errors that are clustered at the region-year level.

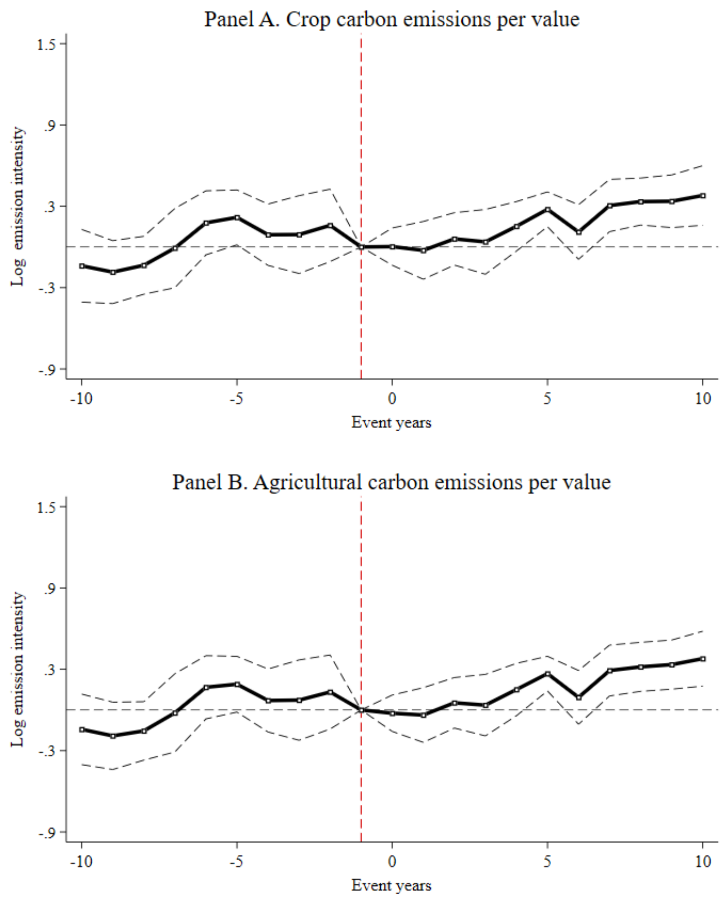

Figure A9: Dynamic effects of GM crop adoption on carbon emissions per value

Notes: This figure presents robustness checks for the event-study estimates presented in Figure 8, using carbon emissions per value of crop production (Panel A) and per value of agricultural production (Panel B) as the dependent variables. The dashed vertical line indicates the year before GM crop adoption. The confidence intervals are computed based on standard errors that are clustered at the region-year level.

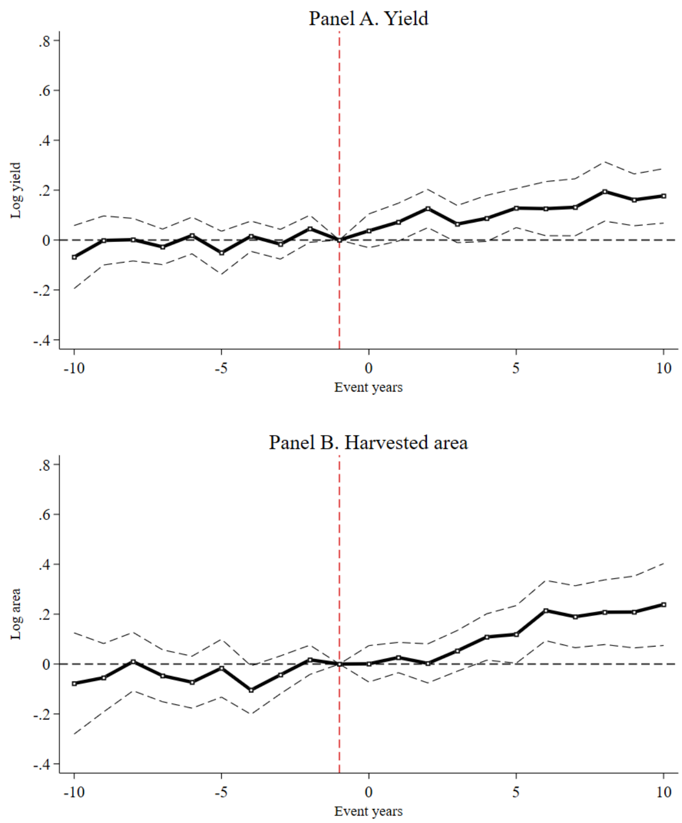

Figure A10: Dynamic effects of the adoption of GM varieties on the yield and harvested area of the four GM crops

Notes: The figure reports the effects of GM varieties on the yield (Panel A) and harvested area (Panel B) of the four GM crops, estimated based on the event-study model (17) using Poisson regression. Standard errors are clustered at the country-crop level.

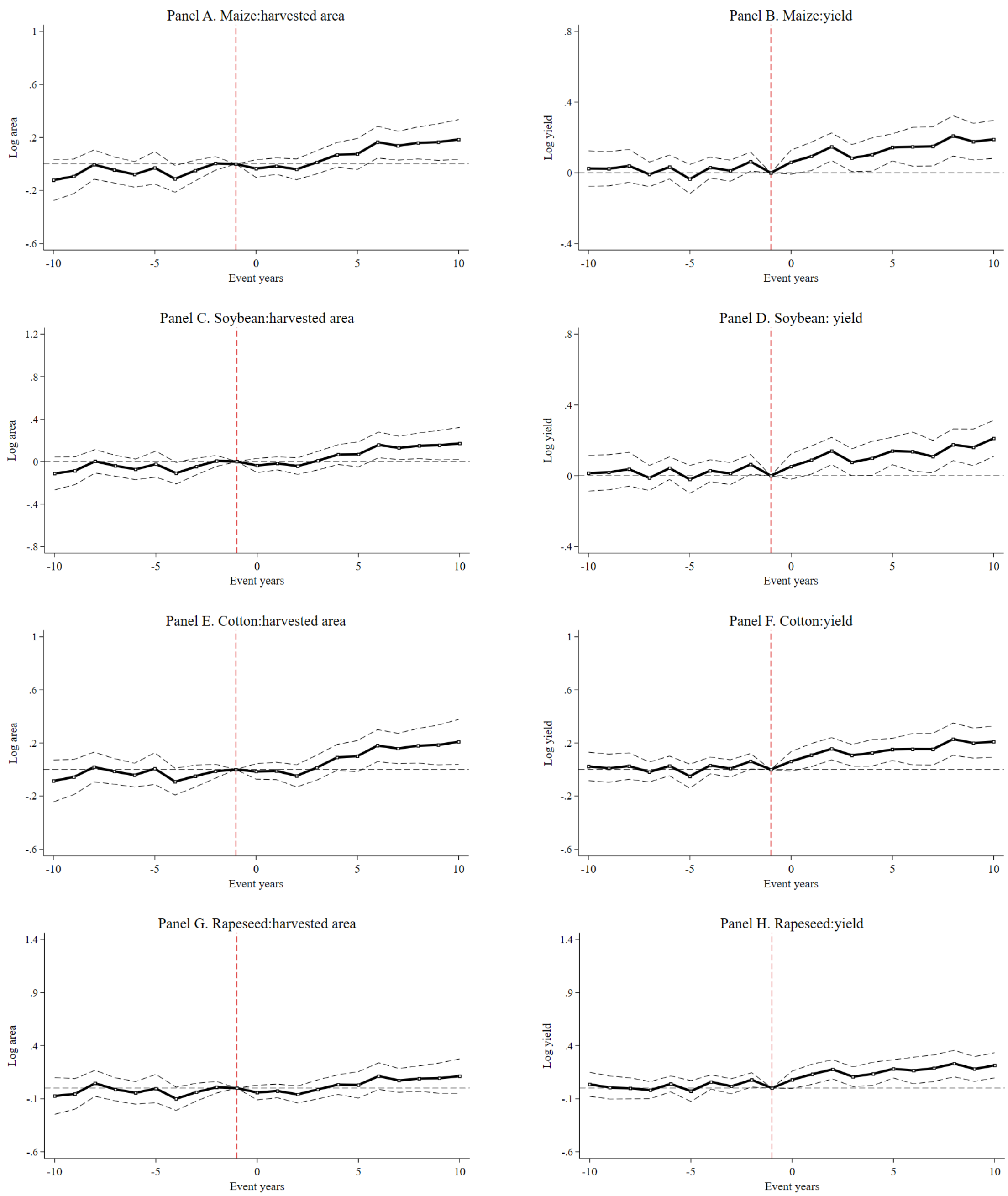

Figure A11: Dynamic effects of the adoption of GM varieties on the yield and harvested area of each major GM crop

Notes: The figure reports the effects of GM varieties on the yield and harvested area of each of the four GM crops, estimated based on a modified version of the event-study model (17) using Poisson regression. Standard errors are clustered at the country-crop level.

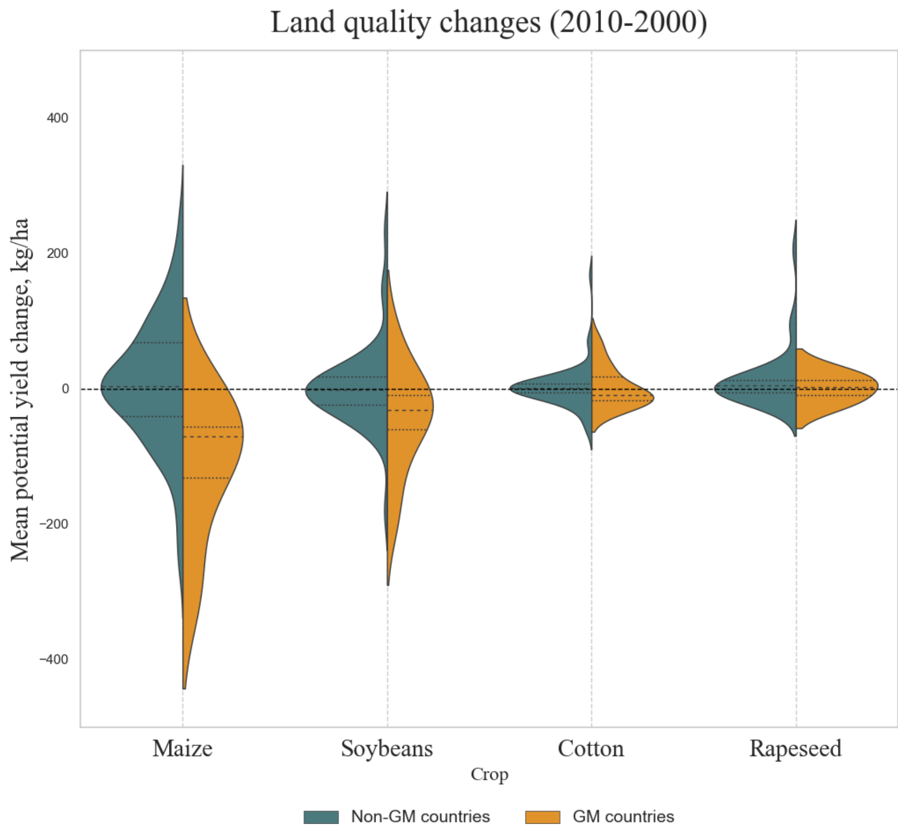

Figure A12: Crop-level land quality changes in GM and non-GM countries from 2000 to 2010

Notes: This figure presents the changes in crop-level attainable yield, a measure of land quality, from 2000 to 2010 in GM and non-GM countries, calculated based on the raster data from the FAO's GAEZ database. GM countries are those that adopted the GM variety of the crop before 2010, while non-GM countries are those that did not.

A.2 Table

Table A1: Details of FAO's calculation of agricultural carbon emissions

Source	**Step**	**Data source**	**Adjustments**
Fertilizer use	Amount of nitrogen fertilizer × emission factor	National agricultural statistics, surveys	Adjustments for local conditions such as soil type or climate
Crop residue burning	Amount of crop residue burned × crop-specific emission factors	National agricultural surveys	Emission factors vary by crop type and regional conditions
Rice cultivation	Area of rice cultivation × emission factors, adjusted for water management and organic amendments	Agricultural census, land use data	Adjustments based on water management (e.g., continuous flooding vs. intermittent drainage) and the type of organic fertilizer applied
Land use changes	Land area converted × emission factors for carbon stock loss	Land-use change maps, satellite data	Adjustments for different land types, vegetation, and soil organic carbon
Livestock	Number of livestock × emission factors for enteric fermentation	Livestock statistics from agricultural surveys	Adjustments based on livestock type (e.g., dairy vs. non-dairy cattle)
Energy use	Amount of fuel (e.g., diesel) consumed × the emission factors for CO_2	National fuel consumption data	Adjustments for fuel type (diesel, electricity) and energy source

Notes: This table summarizes the data sources, main steps, and adjustment factors used in the carbon emission calculations adopted by the FAO, derived from the IPCC Guidelines for National Greenhouse Gas Inventories.

Table A2: Summary of GM crops features and advantages

Category	Features	Maize	Soybean	Cotton	Rapeseed
Herbicide tolerant	HT crops can survive applications of specific herbicides, facilitating weed control without harming the crop.	✓	✓	✓	✓
Insect resistant	These crops produce proteins toxic to certain insects, reducing or eliminating insecticide use. The Bt protein is a notable example, providing protection against pests like the corn borer.	✓	✓	✓	
Stacked trait	Crops with both HT and IR traits, combining weed and pest management in one. This allows more efficient use of inputs, particularly in high-pressure environments.	✓	✓	✓	
Output trait	These traits improve crop characteristics (e.g., drought tolerance or nutritional value) without modifying input needs, making them distinct from input traits.	✓	✓	✓	✓

Notes: This table summarizes the main features and advantages of major GM crops varieties. The data are typically derived from: https://gm.agbioinvestor.com/

Table A3: Summary statistics

Variable	Unit	Obs	Mean	Std.	Min	Max
Total emissions						
Crop	$1000kt$	4675	10.094	28.291	0.006	287.797
Agriculture	$1000kt$	4675	36.144	94.400	0.017	757.510
Livestock	$1000kt$	4675	25.013	64.099	0.017	501.865
Crop emission intensities						
emissions per area	$t/100km^2$	4675	4.142	29.679	0.129	554.244
Emissions per yield	$t/100t$	4675	9.345	30.760	0.350	453.636
Inputs of crop production						
Fertilizer per area	t/km^2	4241	13.303	24.076	0	229.942
Pesticide per area	$10t/ha$	4675	1.245	2.094	0	18.034
Energy per area (carbon equivalent)	kt/km^2	4068	0.417	4.471	0	86.903
Irrigation area	$1000km^2$	4,526	20.587	77.798	0	749.427

Notes: This table reports the summary statistics of main variables.

Table A4: Correlation between the timing of GM crop adoption and determinants of carbon emissions

	(1) Harvested area per capita	(2) Crop output per capita	(3) Agricultural carbon emissions per capita	(4) Carbon emissions per crop area	(5) Carbon emissions per crop yield
Adoption year	0.272	-0.067	0.541	0.402	0.166
	[0.561]	[0.508]	[0.559]	[1.726]	[1.851]
Crop fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	38	38	38	38	38

Notes: This table reports the simple correlation between the year of the first GM crop adoption in a country and the major determinants of carbon emissions: per capita harvested area, per capita crop output, per capita agricultural carbon emissions, per area carbon emissions, and per yield carbon emissions. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A5: Robustness checks of the effect on total agricultural carbon emissions

	(1)	(2)	(3)	(4)	(5)	(6)
	Crop carbon emissions			Agricultural carbon emissions		
	Approval time	Adoption rate	Poisson regression	Approval time	Adoption rate	Poisson regression
$Treat_i^a \times Post_t^a$	0.073***			0.080***		
	[0.023]			[0.026]		
$Treat_i \times Post_t \times GMrate_{it}$		0.112***			0.090**	
		[0.032]			[0.035]	
$Treat_i \times Post_t$			0.060**			0.074***
			[0.026]			[0.023]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,265	4,364	4,364	4,265	4,364	4,364

Notes: This table presents robustness checks for the baseline estimates presented in table 1. Columns 1 and 4 use the approval time of GM crops as the event time. Columns 2 and 5 use the adoption rate of GM crops as the key explanatory variable. Columns 3 and 6 adopt a Poisson regression (without taking log for the dependent variable). Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A6: Effect on carbon emissions from livestock production

	(1) Baseline	(2) Approval time	(3) Adoption rate	(4) Poisson regression
$Treat_i \times Post_t$	0.120***			0.106***
	[0.031]			[0.028]
$Treat_i^a \times Post_t^a$		0.118***		
		[0.026]		
$Treat_i \times Post_t \times GMrate_{it}$			0.123***	
			[0.037]	
Year FE	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes
Observations	4,364	4,155	4,241	4,241

Notes: This table presents the effect of GM crop adoption on carbon emissions from livestock production, estimated based on model (16). Column 1 presents the baseline result using first harvested time of GM crops as the event time. Column 2 uses the GM crop approval year as the event time, column 3 uses the GM crop adoption rate as the key explanatory variable, and column 4 adopts the Poisson regression (without taking log for the dependent variable). Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A7: Robustness checks of the effect on crop carbon-emission intensities

	(1)	(2)	(3)	(4)	(5)	(6)
	Crop carbon emissions			Agricultural carbon emissions		
	Approval time	Adoption rate	Poisson regression	Approval time	Adoption rate	Poisson regression
$Treat_i^a \times Post_t^a$	0.106***			0.102***		
	[0.015]			[0.017]		
$Treat_i \times Post_t \times GMrate_{it}$		0.184***			0.181***	
		[0.020]			[0.026]	
$Treat_i \times Post_t$			0.084***			0.033*
			[0.014]			[0.018]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,265	4,364	4,364	4,265	4,364	4,364

Notes: This table presents robustness checks for the baseline estimates in Table 2. Columns 1–3 present the effects on crop carbon emissions per area, while columns 4–6 present the effects on crop carbon emissions per yield. Columns 1 and 4 use the approval time of GM crops as the event time. Columns 2 and 5 use the adoption rate of GM crops as the key explanatory variable. Columns 3 and 6 adopt a Poisson regression model (without taking log for the dependent variable). Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A8: Robust to excluding top 3 GM crop production countries

	(1)	(2)	(3)	(4)
	Total carbon emissions		Carbon-emission intensity	
	Crop production	Agricultural production	Per area	Per yield
$Treat_i \times Post_t$	0.099***	0.094***	0.129***	0.126***
	[0.026]	[0.024]	[0.017]	[0.018]
Control variables	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	4,343	4,220	4,343	4,343
R-square	0.991	0.991	0.947	0.927

Notes: This table examines the robustness of the baseline estimates in Tables 1 and 2 by excluding top 3 GM crop production countries from the sample (i.e., the United States, Brazil, and Argentina). Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A9: Heterogeneity of the effect on total carbon emissions

	$Index_i$				
	(1) Crop output per capita	(2) Farmland per capita	(3) GDP per capita	(4) Mean temperature	(5) Total precipitation
$Treat_i \times Post_t$	0.100***	0.089***	0.098***	0.077***	0.067**
	[0.033]	[0.024]	[0.023]	[0.029]	[0.028]
$Index_i \times Treat_i \times Post_t$	-0.030	-0.046**	-0.075***	-0.012	0.008
	[0.033]	[0.022]	[0.023]	[0.026]	[0.025]
Control variables	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes	Yes
Observations	4,241	4,241	4,241	4,241	4,241

Notes: This table examines the heterogeneity in the effect of GM crops on carbon emissions with respect to crop output per capita, farmland per capita, GDP per capita, annual mean temperature, and annual total precipitation. We create a dummy variable for each of these moderating variables. The dummy variable equals one for countries with a 1995 value of the moderating variable above the median, and zero otherwise. The dummy variable is then interacted with the DID component of model (16) to examine the effect heterogeneity. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A10: Heterogeneity of the effect on carbon emissions per yield

	$Index_i$				
	(1) Crop output per capita	(2) Farmland per capita	(3) GDP per capita	(4) Mean temperature	(5) Total precipitation
$Treat_i \times Post_t$	0.080	0.149***	0.152***	0.118***	0.095***
	[0.065]	[0.021]	[0.021]	[0.024]	[0.022]
$Index_i \times Treat_i \times Post_t$	0.014	-0.135***	-0.161***	-0.046	-0.003
	[0.069]	[0.027]	[0.029]	[0.030]	[0.028]
Control variables	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes	Yes
Observations	4,241	4,241	4,241	4,241	4,241

Notes: This table examines the heterogeneity in the effect of GM crops on carbon emissions per yield with respect to crop output per capita, farmland per capita, GDP per capita, annual mean temperature, and annual total precipitation. We create a dummy variable for each of these moderating variables. The dummy variable equals one for countries with 1995 value of the moderating variable above the median, and equals zero otherwise. The dummy variable is then interacted with the DID component of model (16) to examine the effect heterogeneity. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A11: Crowding-out effect on the harvested area of non-GM crops

	(1)	(2)
	Harvested area	
	Crops of the same types	Botanically most similar crops
$Treat_i \times Post_{it}$	-0.041**	-0.076***
	[0.018]	[0.025]
Control variables	Yes	Yes
Country-crop FE	Yes	Yes
Year-crop FE	Yes	Yes
Observations	71,611	22,759

Notes: This table presents the effect of GM crop adoption on the harvested area of non-GM crops, estimated based on a version of the crop-level DID model (18) that uses the harvested area of non-GM crops as the dependent variable. Column 1 examines the effect on all non-GM crops of the same types of the four GM crops, while column 2 examines the effect on the 15 crops that are botanically most similar to the four GM crops. The errors are cluster at the country-crop level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.3 An example of carbon emission calculation

Using the calculation of carbon emissions from a single crop as an example, we illustrate how the FAO calculates agricultural carbon emissions. This example provides a structured approach to estimating carbon emissions for crop production in a given country, covering essential processes such as crop residue management, nitrogen fertilizer application, fuel consumption, organic soil management, and land-use change. These steps ensure accurate and consistent emission estimations that align with international standards. More details on the calculation process can be found at https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html.

FAO calculates crop carbon emissions from the following key processes and stages:

Crop Residue Management: The nitrogen content in crop residues is a primary source of N_2O emissions. FAO follows Eggleston *et al.* (2006) guidelines, calculating N_2O emissions based on nitrogen present in crop residues. The nitrogen content is estimated using the formula:

$$N_{\text{residue}} = \text{Harvested Area} \times \text{Yield per Area} \times \text{Nitrogen Content in Residues}$$

FAO applies default emission factors for N_2O emissions from residues and also accounts for methane (CH_4) emissions if field burning of residues occurs.

Synthetic Nitrogen Fertilizer Application: The application of nitrogen fertilizers produces direct and indirect N_2O emissions, another major source of greenhouse gas emissions in crop production. FAO's estimation approach uses nitrogen input data along with IPCC default emission factors to calculate emissions from fertilizer use:

$$\text{N}_2\text{O Emissions (fertilizer)} = \text{Nitrogen Applied} \times \text{EF}_{\text{fertilizer}}$$

where $\text{EF}_{\text{fertilizer}}$ represents the emission factor for fertilizers.

Management of Organic Soils: For crop production on organic soils (e.g., peatlands), decomposition of soil organic matter leads to N_2O and CO_2 emissions. FAO estimates these emissions based on default emission factors specific to organic soil types.

Fuel Consumption in Machinery: Fossil fuel combustion in agricultural machinery used for planting, harvesting, and transportation contributes to CO_2 emissions. FAO includes emissions from fuel consumption by applying fuel usage rates and emission factors:

$$\text{CO}_2 \text{ Emissions (fuel)} = \text{Fuel Consumed} \times \text{CO}_2 \text{ Emission Factor}$$

Land-Use Change (if applicable): When crop cultivation involves converting forests, grasslands, or other natural ecosystems, emissions due to soil and vegetation carbon loss must be considered. FAO uses IPCC default coefficients to account for emissions from these land-use changes.

Finally, the total carbon emissions from all relevant processes are calculated by summing the emissions of each greenhouse gas (CO_2, CH_4, N_2O) and converting them using global warming potential (GWP) factors from the IPCC Fifth Assessment Report:

$$\text{Total CO}_2\text{-eq Emissions} = \text{CO}_2 + \text{CH}_4 \times 25 + \text{N}_2\text{O} \times 298$$

where 25 and 298 are the GWP factors for CH_4 and N_2O, respectively.