Agricultural input prices and deforestation: evidence from Colombia.

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Agricultural Input Prices and Deforestation: Evidence from Colombia *

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Abstract

Improving agricultural productivity is necessary for economic development. However, disparities in input price shocks could induce disturbances in land use decisions, increasing the demand for land at the expense of forest conservation activities. To investigate this, I employ a synthetic difference-in-differences (SDID) strategy taking advantage of subnational variation in fertilizer dependence in Colombia, after an unprecedented price shock due to a worldwide supply decline in 2021. Results suggest a reduction in deforestation on fertilizer dependent municipalities after the price increase. Municipalities with a higher reliance on fertilizer for agricultural production experienced a reduction of 50 percent with respect to the average deforestation rate. Specifically, I show how the reduced input demand decreased agricultural expansion within the agricultural frontier, providing evidence about how the value of the land affects landowner conservation decisions.

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1 Introduction

Increasing food production while reducing greenhouse emissions remains one of the major sustainable development challenges. To meet the demand from 9.87 billion people in 2050, global food output must rise by approximately 50% (WRI, 2016). However, agricultural expansion has significant environmental consequences.Agricultural deforestation contributes more carbon dioxide emissions than the entire ground transportation and airline fleets (IPCC, 2023). Moreover, agricultural expansion cleared 30% of Latin America's forest cover between 2001 and 2015 (Curtis et al., 2018). Despite this, concerns over food security and economic growth often sideline deforestation in climate policies. Intensification practices, especially through fertilizers and modern inputs, aim to boost yields without expanding farmland (Garcia, 2020; Foster and Rosenzweig, 2007). Since input adoption introduces changes on agricultural land use decisions, the deforestation consequences of price shocks remains a complex empirical question.

Do agricultural input price shocks influence deforestation and farmers conservation decisions? I examine this question using the exogenous fertilizer price increase in Colombia, caused by the Russia-Ukraine invasion, as a natural experiment. This shock doubled prices for the country's most used fertilizer types. Using a synthetic difference in differences (SDID), I estimate the differential change on deforestation of municipalities with the highest fertilizer (above the 75th percentile) demand prior to the price shock. This involves comparing municipalities with high exposure (treated) to those with low exposure (control) to the shock, before and after the price increases.

Despite its clear role in agricultural policy, the study of the environmental effects of intensification practices shows mixed theoretical and empirical results, specifically on the case of its impact on land usage. First, increases in productivity per land unit can reduce the demand of land when introducing new inputs like fertilizer, reducing deforestation (Abman and Carney, 2020; Foster and Rosenzweig, 2007). On the other hand, productivity increases due to intensification can increase the profitability of agricultural activities and hence increase the demand for all inputs including land, threatening forests (Angelsen and Kaimowitz, 2001). This debate is known in the literature as the Borlaug-Jevons debate. (Hertel, 2012).

Specific characteristics of fertilizer supply chain impose an impediment for its adoption mainly in developing countries. Being a capital-intensive industry with economies of scale has concentrated production geographically (Hernandez and Torero, 2013), where half of the production is controlled by top 5 countries (and a few firms inside of them). Concentration makes developing countries highly dependent on imports. In particular, no other region depends more on imported fertilizer than Latin America and the Caribbean (CEPAL et al., 2022). The region imports about 85% of the fertilizer used, from which a fifth comes from Russia (world largest producer). These factors difficult farmers' obtention of these inputs and make the region vulnerable to external shocks. In the Colombian context, 98% of the base nutrients for fertilizer production is imported. According with the Agriculture Ministry, by 2020 more than 40% of the imports of fertilizer came from Russia (22%) and the United States (19%).

The Russia-Ukraine conflict severely disrupted global fertilizer supply chains. Mainly because of Russia being one of the largest producers of all the nutrient varieties of fertilizer [1]. Supply reduction due to war sanctions and export restrictions induced other producer countries to restrict their exports of fertilizer in order to secure domestic markets. In this way, not only the direct importers of Russia's fertilizer were affected, but all the countries that rely on imports of these inputs (Hebebrand and Glauber, 2023). This shock induced significant price increases between 2021 and 2022 climbing to highest levels since 2008 food crisis (Hebebrand and Laborde, 2022).

Using agricultural census data, crop-specific fertilizer use, and satellite imagery of forest loss, I find that deforestation declined after the price shock in municipalities more reliant on fertilizers. To test whether price shocks alter land use decisions within farms, I leverage agricultural frontier maps to track deforestation inside designated agricultural areas. Consistent with higher input prices reducing farm profits and land demand, the decline in deforestation was more pronounced within the frontier. This suggests that input price shocks influence farmers' forest conservation

[1] N, for nitrogen; K, for potash; P, for phosphate

decisions. My preferred estimate indicates a 68% reduction in in-frontier deforestation relative to its pre-shock mean.

The evidence presented in this paper aligns with the expanding literature dedicated to documenting the relationship between trade, agricultural activities and deforestation (Grag et al., 2024; Jayachandran, 2022; Hsiao, 2021; Grossman and Krueger, 1991). Specifically, this paper contributes the literature trying to estimate the effect of agricultural prices on farm level forest clearing decisions. This literature focuses on how the prices of potentially substitutes of forest conservation incentivize transition at the expense of forest loss, this can include wood prices (Chimeli et al., 2012) prices of agricultural output (Krah, 2023; Harding et al., 2021; Assunçao et al., 2015) or, even relative prices between agricultural and more extensive economic activities as cattle raising (Braganca, 2018). This paper contributes with evidence regarding input prices, as opposed to the output prices, effects on land use decision.

This paper also contributes to understand the implications of the incorporation of intensification practices and its effects on forest loss. Previous work has been divided into two competing theories. Part of the literature finds that increasing crop yields could induce a decrease in prices and therefore the demand for more land (Pelletier et al., 2020; Tscharntke et al., 2012) . Some articles argue that intensification can make agriculture more profitable and hence increase the need to replace forests with crop land (Szerman et al., 2022; Villoria et al., 2014). Additionally, previous work on fertilizer has focused on the effect of its adoption trough randomized controlled trials (RCTs) as in Duflo et al. (2011). My article examines the dynamics of deforestation when intensification practices are in place and agricultural production becomes reliant on these products. This also aims to contribute empirical evidence to address the policy recommendations proposed in the previous literature on strategies to achieve sustainable and successful intensification practices.

Finally, this paper discusses agriculture as an economic driver of deforestation in Colombia. Most of the research has focused on deforestation as a consequence of civil conflict (Prem et al., 2020; Fergusson et al., 2014, 2020). Research has also highlighted how the profitable transition to other activities has increased deforestation in the country even in a post-conflict era, mostly translated into land intensive activities in areas previously inaccessible due to conflict (Murillo-Sandoval et al., 2023; Gonzalez and Komisarow, 2020). These articles highlight how economic incentives, institutional context and state capacity have contributed the most on Colombia's forest loss. My core analysis evaluates the effect of agricultural practices and its contribution to deforestation in Colombia, specifically on the effects of the vulnerability of agricultural sector to external shocks building in previous work for other countries (Carreira et al., 2024; Mata and Dotta, 2021).

The remainder of the paper is organized as follows. In the next section, I present the context of the natural experiment. Potential mechanism discussion is discussed in Section 3. Section 4 describes the empirical design and data. Section 5 presents the empirical strategy. Section 6 presents the results. Section 7 concludes.

2 Context

2.1 The effect of Russia-Ukraine conflict in agrochemical industry

Most of the literature describes fertilizer's as a highly concentrated market (Hernandez and Torero, 2013). Concentration and consolidation can be mainly attributed to the industry's high requirement of raw inputs like phosphate rocks, potassium salts and natural gas, as well as the prevalence of economies of scale and capital intensity in production (Bumb and Gregory, 2006). The three most important nutrients produced by the fertilizer industry are specifically concentrated in some regions, determined by their access to input deposits. Nitrogen is mostly produced in East Asia, phosphate on North America and East Asia and most of the potash is produced in East Europe, Central Asia and North America (Hernandez and Torero, 2013). Also, concentration patterns are translated into within-country concentration: for most of the top producing countries, half of the production is controlled by the top four firms. Indeed, for the case of Russian and Belarus specifically, in the potash market the top-4 firms cover the entire production of this nutrient.

Russia's invasion of Ukraine in 2022 further exacerbated the already escalating fertilizer prices. In 2020, Russia and Belarus were the world's most important fertilizer exporters. These two countries covered the 20 percent of the worldwide production, followed by China (12%), Canada, United States and Morocco. With the war, most producer countries opted for imposing restrictions on fertilizer trade on Russia and Belarus, including even banking regulations or insurance costs that impeded trade with the producers from these countries. The need of other countries to secure their fertilizer supply led to export restrictions, which, in turn, reduced overall fertilizer trade (Hebebrand and Glauber, 2023).

In Colombia, approximately 2 million metric tons of fertilizer are consumed annually, with a significant portion being inorganic fertilizer. From these, 75 percent was imported from Russia (29%), Venezuela (20%), Trinidad and Tobago (14%) and Ukraine (13%). For 2021, 44 million USD of Russian fertilizer where imported, representing 22% of the import market share of the country (International Trade Administration, 2022). The fertilizer supply reduction implied several shocks on the prices of the most relevant fertilizer used in the Colombian agricultural sector. Figure 1 shows that the fertilizer price index, which accounts for relative importance of varieties, increased by about 103,3% from March 2022 with respect to the last year. This increase affected the production of the main crops in Colombia as potato, coffee, cocoa, oil palm, banana and sugar cane, in which fertilizer implied between 20 and 30 percent of the total production costs (Banco Agrario, 2008).

2.2 Agriculture and deforestation in Colombia

The agricultural, forestry and other land use (AFOLU) sector is the main source of CO2 emissions in Colombia, accounting for 59 percent of the total emissions in 2018 (IPCC, 2023). Within this sector, changes in land use represent 30 percent of the country's emissions. The contribution of Colombia to global deforestation is more than proportional to its area and reducing deforestation rates is one of the biggest governmental objectives (Ideam et al., 2021). Illegal land grabbing, cattle raising, illegal infrastructure and mining, and illegal crop cultivation are the main drivers of deforestation. The majority of deforested areas are converted into grasslands, with only 7 percent used for cultivation. The forest area lost between 2016 and 2021 comprehends a similar area to that of countries like Qatar or Jamaica [2]. Deforestation in Colombia is mostly concentrated in the Amazon region, accounting for approximately 65 percent of the national deforestation each year between 2016 and 2021 (FCDS, 2023).

2.3 Mechanisms – Fertilizer usage and deforestation

Theoretical and empirical studies on the effects of intensification practices show divergent results. Increasing land productivity on cultivated land may reduce or prevent further deforestation, but research suggests the phenomenon is more complex.(Villoria, 2019; Villoria et al., 2014). Productivity increases caused by the technological improvements can alter the relative expected profit of agricultural activities with forest conservation or other land uses. This debate has been titled in the literature as the Borlaug- Jevons debate, highlighting the diverging results of efficiency increases on input usage. Borlaug (2007) found that cereal production intensification, mainly driven by the introduction of fertilizers on the 1950 Green Revolution, saved a billion of hectares from being deforested. Jevons,in 19th century, describes a similar situation in which improvements on coal productivity implied an increase in its usage.

In this framework, there exist two conflictive effects of input prices on forest clearing decisions. In particular, for the fertilizer case, higher prices can influence farmers to substitute for another inputs, increasing labor or adopting more extensive production systems, causing deforestation (Angelsen and Kaimowitz, 2001). Higher production costs may also reduce agricultural activities' profitability and hence reduce the extent of land used for agriculture. In both cases, the effect is directly affected by the substitution elasticity between inputs, as highlighted by Villoria (2019). In the case of deforestation, land- forest substitution elasticity is determined by the distance to the agricultural frontier of the affected farms or the "tightness" of land constrains within a municipality (Assunçao et al., 2015).

To account for the importance of land endowment and restrictions for deforestation, I provide differential analysis for municipalities with different forest levels, road density, state presence and conservation policies.

[2]Data from the Carbon and Forest Monitoring System from IDEAM (Sistema de Monitoreo de Bosques y Carbono)

3 Data

Data consists on a municipality-year panel dataset covering the 2014-2023 period. The sample includes all Colombian municipalities with agricultural activity and forest. Since unobserved factors can bias the results, fertilizer intensity and municipality characteristics are measured on the period previous to the time range studied. Table 1 shows descriptive statistics of the main variables and fertilizer prices.

3.1 Deforestation

The primary outcome analyzed in this paper is the deforestation rate. I obtained forest cover loss data from Hansen et al. (2013) through the Global Forest Watch (GFC) portal. This dataset consists of 30 x 30-meter resolution satellite imagery of global vegetation losses. GFC use by its own might lead to wrong conclusions as highlighted by Fergusson et al. (2020) (mainly driven by remote sensing data prediction of certain types of plantations as trees). To overcome this bias, I employ the 2017 forest cover dataset provided by Colombia's Institute of Hydrology, Meteorology and Environmental Studies (IDEAM by its Spanish acronym) in which satellite data passes through expert validation. I consider only Hansen deforestation over validated forest lands.

3.2 Agriculture

Data on farm level agricultural sector is obtained from the 2014 Agricultural National Census (CNA by its name in Spanish) provided by the National Administrative Statistics Department (DANE). This dataset covers 98,9% of the Colombian agricultural sector and reports information about farmland, crops, socioeconomic characteristics and employed inputs as machinery, fertilizer, improved seeds, etc. Among all these variables, CNA reports at the farm level the planted area for each crop.

I also obtained geographical delimitation of the Colombian agricultural frontier from the Unit of Rural Planning (Unidad de Planificación Agropecuaria, UPRA) [3]. In Colombia, the agricultural frontier covers 42.944.940 Ha, representing 36.7% of the entire land, shown in Figure 2.

[3] In the Colombian law, the National Agricultural Frontier "is the limit of rural land, that divides the areas where agricultural activity, conditioned areas, and areas of special ecological relevance where agricultural activities are excluded by the rule of law". Resolución MADR 261 de 2018

3.3 Fertilizer use

I use an expert survey conducted by the International Fertilizer Development Center and the International Fertilizer Association to construct chemical fertilizer usage by crop for Latin America. Latest round includes data for 2017 and 2018. Crop-level requirements are reported as fertilizer metric tons per cultivated hectare. This regional-level measure is assigned to the 30 most important crops in Colombia , according with the categories specified in Ludemann et al. (2022). Table 1 displays list of crops and their fertilizer requirements.

3.4 Other variables

In addition to forest and agricultural-related variables, I employ within-municipality variation on the presence of protected areas obtained from the National Unique Registry of Protected Area (RUNAP) which includes all the legally declared conservation areas before 2019. I also include geolocated information on national roads obtained from Colombian Road Institute (INVIAS) which includes both primary and secondary roads.

4 Methodology

4.1 Empirical Strategy

My empirical strategy uses cross-sectional variation based on the hectares of cultivated area that report using fertilizer across all municipalities. I consider only municipalities in which the cultivated area used for the 30 selected crops cover at least 50 percent of the entire cultivated area. I compare deforestation across municipalities with high dependence on fertilizer against those with low dependence before and after the 2021 price shock. To determine which municipalities relied more on fertilizer and where thus more affected by the increased costs, I adapt the methodology employed by Ghose et al. (2023) and calculate the following index of municipality-level fertilizer usage:

$$FI_m = \sum_{c=1}^{30} FIC_c \times \frac{\sum_{i=1}^{n} A_{imc}^{2014}}{\sum_{i=1}^{n} A_{im}^{2014}} \tag{1}$$

Where c indexes crop, m denotes municipalities ,i denotes a productive unit (farm). FIC_c

denotes fertilizer intensity of crop c and A_{imc}^{2014} denotes the cultivated area of crop c by farm i at municipality m. Ranking municipalities by this fertilizer usage index, I select as treated those municipalities on the top-25 of the empirical distribution. Figure 3 depicts the distribution of this measure and the cutoff to which units are selected. Since this measure is calculated before my treatment year , it accounts for potential endogeneity due to changes on fertilizer adoption correlated with deforestation. Figure 4 displays the geographical distribution of treatments status.

My empirical strategy follows a synthetic differences-in-differences (SDID) strategy, suggested by Arkhangelsky et al. (2021). Due to different characteristics on treated and control municipalities previous to 2021, it can be expected that parallel trends assumption might be threatened which might lead to the wrong conclusions when estimating the effect of price shocks on deforestation, as highlighted by Roth (2022). Figure 6 shows the evolution of the average outcomes by year on treatment and control municipalities. SDID offers advantages in this setting by re weighting each control municipality m by $\hat{w_m}$ such that pre-trend outcomes are parallel to those of treated municipalities. Figure 5 displays the unit-specific weights for control municipalities for both outcomes. Additionally, finds weights λ_t for each year so that average outcomes post treatment on low-intensity municipalities differ by a constant from the weighted average of the pretreatment outcomes on the same municipalities. Together, weights make the following two-way fixed effects non-parametric estimation more credible.

$$Y_{m,t} \;=\; \alpha_t + \;\beta_m + \;\gamma(FI_{m,2014} \times Shock_t) + \epsilon_{e,t} \tag{2}$$

Where $Y_{m,t}$ denotes the hectares deforested (in logarithm) or the deforestation ratio (relative to 2017 forest) at year t by municipality m, α_t and β_m denote year and municipality fixed-effects respectively. $FI_{m,2014}$ is a dummy indicating if municipality m is above the 75th percentile of fertilizer intensity in 2014[4]; $Shock_t$ is a dummy that indicates if deforestation took place after 2021. γ is the parameter of interest that captures the differential effect of fertilizer price shocks on deforestation on municipalities that rely more on fertilizer. Figure 7 shows the evolution of the average deforestation ratio by year on treatment and control municipalities using SDID weights and high-

[4] I include placebo-robustness checks altering this definition

lights the effectiveness of the method on fulfilling the parallel trends assumption. To account for any aggregate department-level time shock, I also include department-time fixed effects θ_{dt}.

4.2 Other specifications

I estimate a set of different equations from the main specification to get a better understanding of potential mechanisms behind the results. First, I augment Eq. 2 to confirm the hypothesis that the effect of price shocks might be dependent on the forest endowment of each municipality and on the institutional constraints to deforestation. This is done by including a third interaction term of characteristic Z_m, which denotes a dummy variable indicating that municipality is above the median of the distribution of forest share, road density [5] and the share of protected area.

$$\begin{aligned} Y_{m,t} = &\alpha_t + \beta_m + \gamma_1(FI_{m,2014} \times Shock_t \times Z_m) \\ &+ \gamma_2(FI_{m,2014} \times Shock_t) + \gamma_3(FI_{m,2014} \times Z_m) + \epsilon_{e,t} \end{aligned} \tag{3}$$

5 Results

5.1 Main results

Table 3 presents the results of estimating Eq. 2. In the first column, I present the differential effect of the price shock on the deforestation ratio. Column 2 depicts the effect on the (log) hectares deforested on municipalities with a higher exposure on fertilizer. Results indicate that fertilizer price shock implied a significant reduction of deforestation on more dependent municipalities. First column point estimates show an approximate 47% decline on the deforestation rate, compared to the mean deforestation ratio before 2021. In the second column, estimates indicate a 5 percent decrease on the log hectares deforested with respect to the mean. The inclusion of department-time fixed effects implies an slightly-significant negative effect on deforestation, suggesting that this results cannot effectively by separated from department-level shocks.

Figure 7 show the evolution of the main outcomes variable across treated and control municipalities, using the same weights as in Eq. 1. Moreover, comparing the deforestation series in 6

[5] In this case, road density is measured as kilometers per hectares.

with constant weights, allows to highlight the effectiveness of the method in overcoming possible parallel trends violation.For the case of deforestation ratio, notice how the SDID weighting yields almost identical trends for both groups even when only parallel trends were needed. We can observe a differential decline on treated municipalities on both outcomes after 2021 when the shock took place. Overall, these results show that,on aggregate, mostly-affected municipalities may have experienced the same or lower deforestation rates after the fertilizer's price increase which highlights the potential effect of price shocks on forest clearing.

To understand and locate deforestation I intersect deforestation data with the legal definition of the agricultural frontier and calculate deforestation on both sides of its boundaries. Table 4 shows the differential effect on deforestation inside and outside the agricultural frontier. Results suggest that this decline in deforestation took place mainly inside the agricultural frontier. These estimates are significant in magnitude, Column 1 shows that the deforestation ratio inside the agricultural frontier decreased by about 100 percent from its pre-shock mean. On extension, deforestation inside the frontier was reduced by 8 percent with respect to the average deforested log hectares. The inclusion of department-time fixed effects yield similar results, suggesting that the effect on deforestation is not induced by state-specific shocks, such as conflict or consumer-side effects. Figure8 show the weighted series of both ratio and log hectares inside the agricultural frontier. This change suggests that forest inside agricultural units was prevented from being deforested due to the overall increase of the costs for agricultural production. Furthermore, these findings suggest that fertilizer scarcity may not be effectively compensated through land employment and that the potential productivity losses may have been compensated trough price increases or the incorporation of other inputs.

The magnitude of these results in deforestation is in line with other articles related to deforestation in Colombia. Taking as reference the result in column 1 from Table 3 and combining average deforestation rate and forest hectares, an average municipality losses 115 hectares each year. The magnitude of the estimated effect suggests that the reduction due to the price shocks being about 54 hectares. For instance Prem et al. (2020) find an average increase in deforested area of 30 hectares after a ceasefire declaration in 2014 [6].

[6] $0.161\% \times 72000$ Ha. $= 115.92$ Ha. ; $47\% \times 115.92$ Ha. $= 54.48$ Ha.

5.2 Mechanisms

Previously exposed results suggest that the increased costs may have reduced the demand for land and hence, reduced deforestation. Two mechanisms may explain this relationship. Evidence regarding them is displayed in Tables 5 to 7. As stated formerly, one of the main theoretical determinants of deforestation is landholder's land expansion capacity. Mainly, this capacity can be determined by the endowment of forest over which agricultural activity can be expanded. If municipalities are mostly dedicated to agricultural activity and no land remains as forest prior to the shock, there is no expansion capacity and no plausible effect on deforestation. Column 1 in each table shows the results from the estimation of Eq. 3 in which Z_m indicates if a municipality had a high share of forest prior to the shock.

The reduction of deforestation inside the agricultural frontier is the more interesting results and hence makes heterogeneous effects in Table 6 over this area the most relevant for the scope of this paper. The triple interaction on Panel A suggests that municipalities with a forest endowment above the median had a significant decrease in deforestation ratio. Conversely, the sum of coefficients on Panel B depicts an increase on the hectares deforested on highly exposed municipalities with a high forest endowment. However, in both panels the test of the sum of coefficients suggests a null effect .These results combined suggest that the increased fertilizer price had no differential effect in municipalities with higher forest endowment, municipalities that were expected to have an increase in deforestation after 2021.

Another possible impeller mechanism for deforestation can be attributed to the presence of roads that facilitate access to forests. Column 2 in Table 6 shows the heterogeneous results over treated municipalities with a high road density. As shown in Panel A, there is no differential significant effect over this set of municipalities after the price shock. The last mechanism is related to institutional factors and state capacity. If conservation policies are well-enforced, cropland expansion should not be observed on municipalities with high state capacity or presence of the enforcer institutions. However, since agricultural frontier excludes protected areas, there should not be an effect on this type of deforestation. Column 3 displays heterogeneous effects between municipalities with a high share of protected areas relative to municipality's area. In this case, results suggest no differential effect on the deforestation ratio over municipalities where conservation policies can be better enforced, as shown in Panel A.

5.3 Robustness checks

Exercises to strengthen the robustness of my results were conducted. Tables 8 and 9 present these exercises for the main specifications. To understand the degree of localization of the results due to SDID weighting, a common exercise compares this estimator with a standard DID (Difference in Differences). Columns 1 and 2 in Table 8 show the effect on the deforestation ratio and the hectares deforested, respectively. Both the effects on intensive and extensive deforestation seem robust, as estimates show almost a similar magnitude to the ones presented in the main results.

Due to the possible bias on the previous results induced by the presence of outliers and the heterogeneity of forest distribution across Colombia, I conduct the same previous analysis excluding municipalities below the 10th and above the 90th percentile of the empirical forest distribution. Table 9 presents this later version of the results. These results provide evidence that the previous results are not driven by some specific type of municipalities. This exercise is mostly more relevant on the effect on hectares deforested which is more sensitive to outliers.

In addition, I explore alternative percentile cutoffs for classifying treated municipalities. Figure 10 shows the estimated coefficients and their respective 90 and 95 percent confidence intervals. These results suggest that the effects, both in the scaled and unscaled measures, are solid regardless of the percentile to assign municipalities to the treatment group.

6 Concluding remarks

Fertilizer price shocks induce significant challenges to the Colombian agricultural sector, mainly explained by the country's dependence on this input's imports. The common debate on agricultural production relates the potential effects that an unexpected shock on the agricultural sector might have over environmental factors. Specifically, my findings indicate that this shock led to a decrease on the deforestation practices where fertilizer was more relevant for agricultural production. Although multiple mechanisms can explain this phenomenon, this paper shows that these results might be driven by a decreased in the demand for land by agricultural producers. Additionally, I show how these results were not affected by institutional and physical factors that might facilitate and improve the capacity of land expansion.

This study aims to capture the environmental effects of increased input prices and agricultural intensification in a context where import substitution is not possible due to production capacities. The results exposed in this article provide evidence on how input prices influence deforestation. In this case, high fertilizer prices reduced deforestation by increasing the overall cost of agricultural activity. From a policy perspective, these results highlight the importance of incorporating the expected return from land expansion into conservation policies. This analysis sheds light of price monitoring to align the incentives of landholders with forest conservation. However, this study does not show evidence on whether these decline in deforestation implied general increases in welfare. Beyond the scope of this paper is to analyze this general equilibrium effects.

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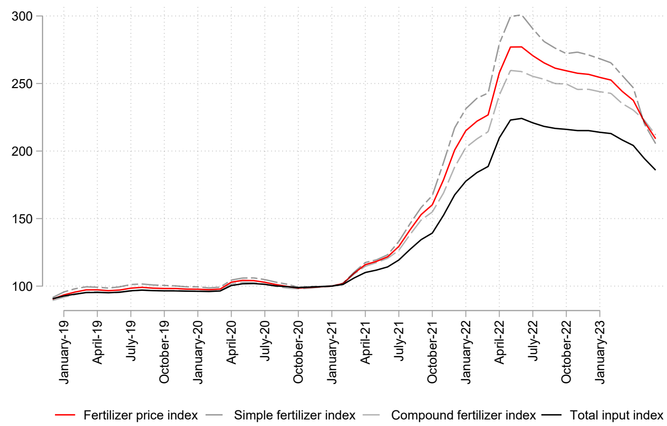
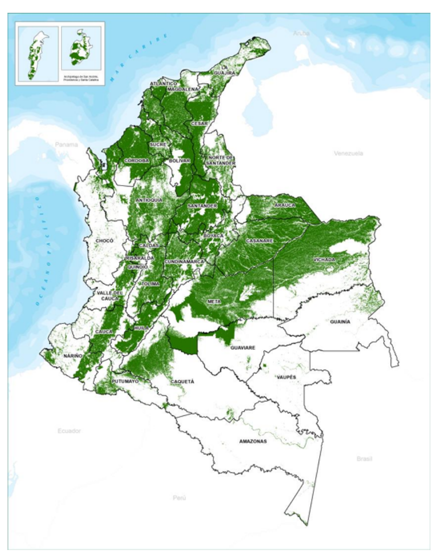
7 Figures and tables

Figure 1: Evolution of fertilizer prices in Colombia



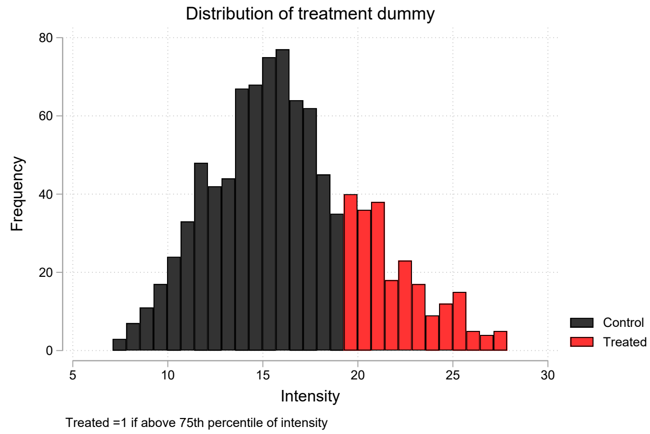
Notes: This figure displays the evolution of the input price index calculated by DANE. Weighted by national sales by variety. The red line shows the index calculated only for fertilizer. Dashed gray lines present it disaggregated by simple and compound varieties. Black line displays the index calculated with all agricultural input, including pesticides and balance feed.

Figure 2: Colombian agricultural frontier. UPRA



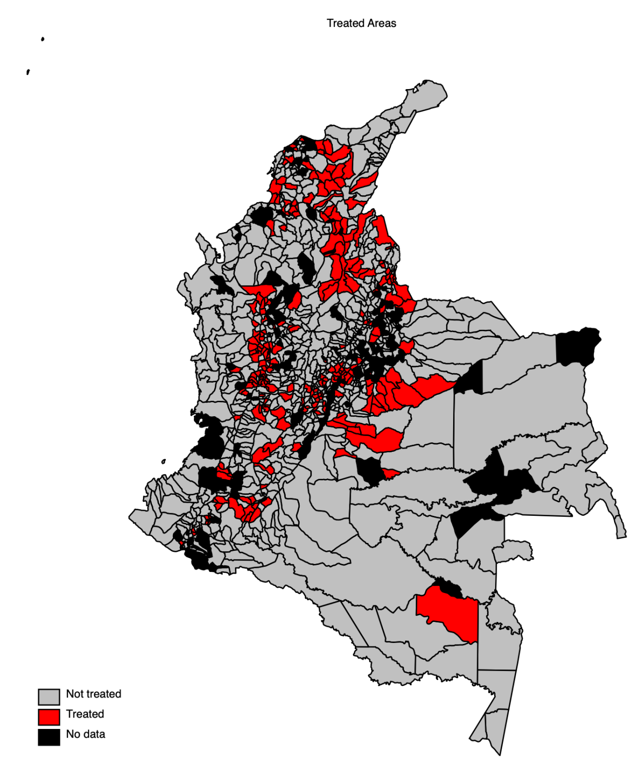
Notes: This figure presents the delimitation of Colombian Agricultural frontier. In the Colombian law, the National Agricultural Frontier "is the limit of rural land, that divides the areas where agricultural activity, conditioned areas, and areas of special ecological relevance where agricultural activities are excluded by the rule of law". Resolución MADR 261 de 2018

Figure 3: Treatment assignment



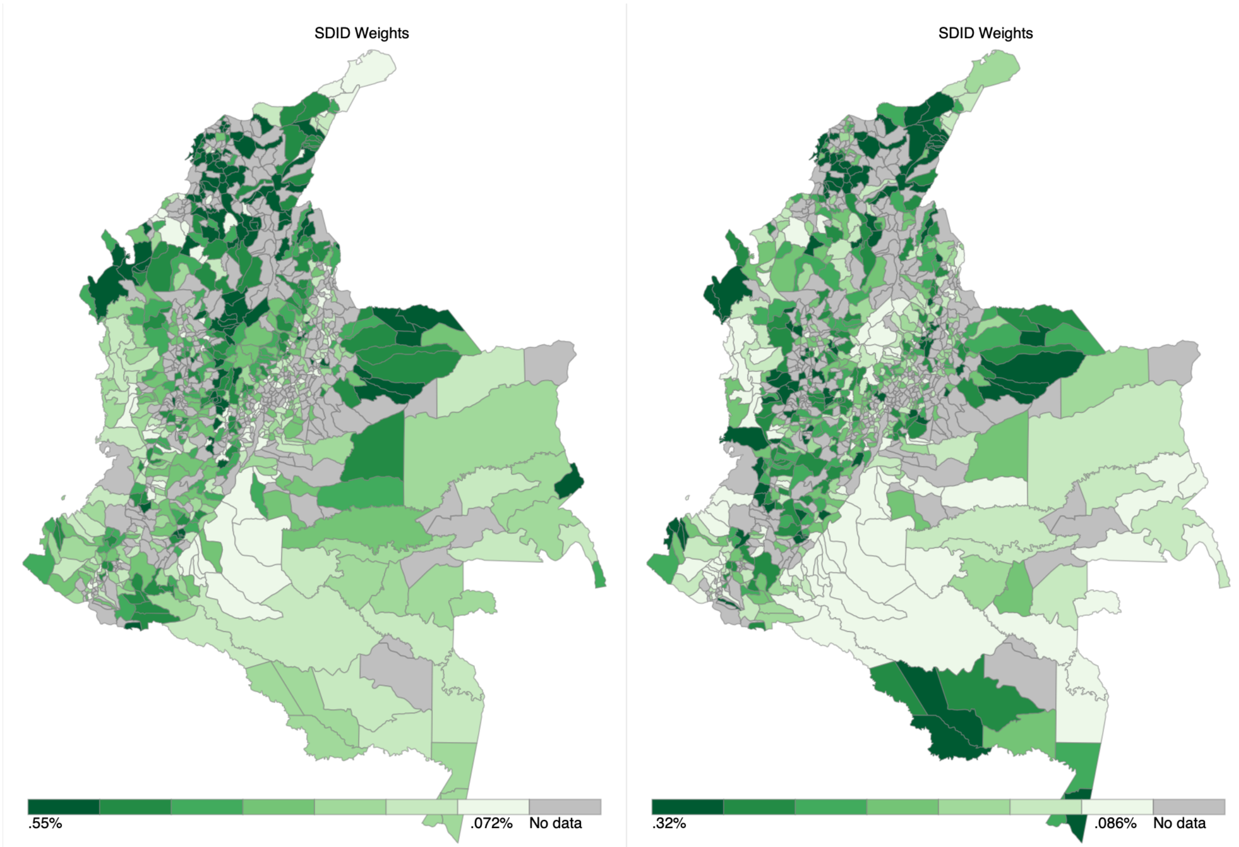
Notes: This figure displays the distribution of fertilizer intensity measured in 2014. Red bars highlight municipality-level fertilizer intensity for municipalities above the 75th percentile.

Figure 4: Treatment assignment. Geographical distribution



Notes: This figure displays the geographical distribution of treatment status. Treated municipalities in red.

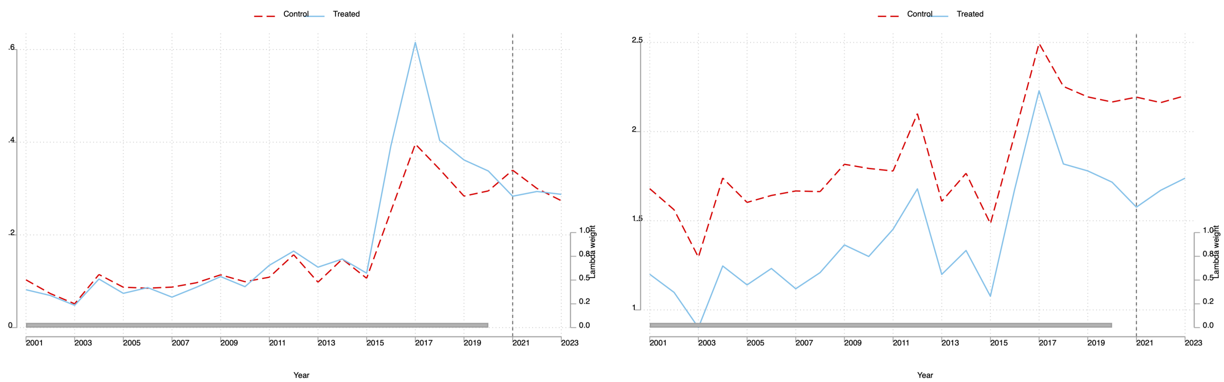
Figure 5: Unit-specific SDID weights



(a) Deforestation ratio (b) Ha. deforested (log)

Notes: Each figure displays the corresponding unit-specific weights for control municipalities in the main specification. Darker color implies units that receive higher weights to make average outcome parallel to the average outcome on treated municipalities.

Figure 6: Deforestation series with constant weights. Entire forest area.



(a) Deforestation ratio

(b) Ha. deforested (log)

Notes: Each panel displays the corresponding series for control and treated municipalities. Vertical red line highlights the year of the price shock. Blue line represents the evolution of each outcome for treated municipalities. Red dashed line represents the evolution of each outcome for control municipalities.

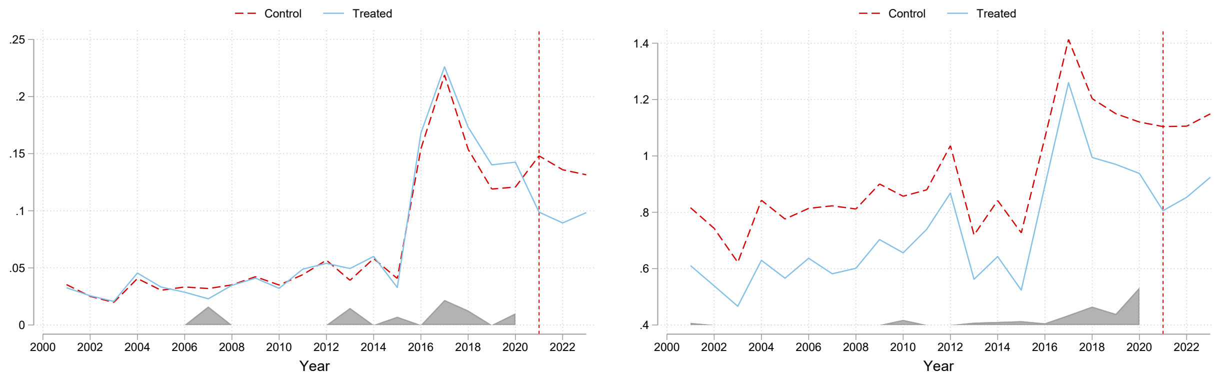
Figure 7: Deforestation series. Entire forest area.

(a) Deforestation ratio

(b) Ha. deforested (log)

Notes: Each panel displays the corresponding series for control and treated municipalities as proposed by Arkhangelsky et al. (2021). Vertical red line highlights the year of the price shock. Blue line represents the evolution of each outcome for treated municipalities. Red dashed line represents the evolution of each outcome for control municipalities.

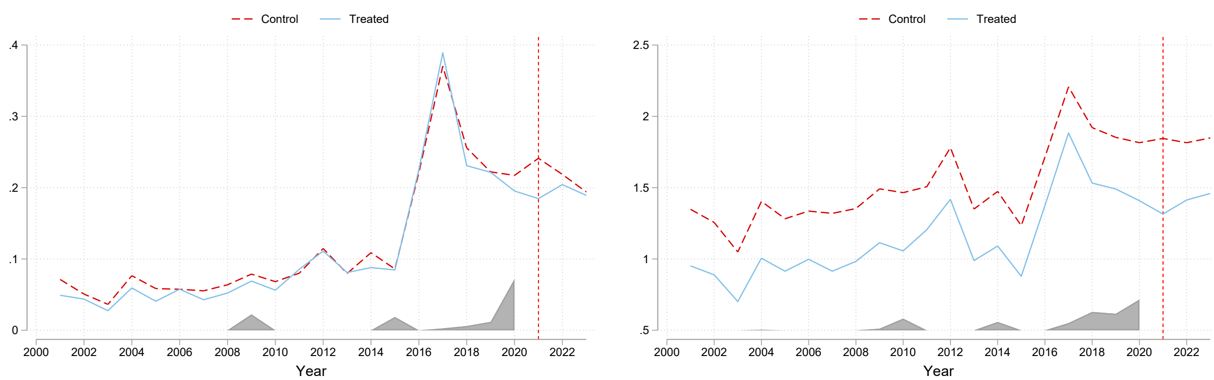
Figure 8: Deforestation series. Forest inside agricultural frontier.



(a) Deforestation ratio (b) Ha. deforested (log)

Notes: Each panel displays the corresponding series for control and treated municipalities as proposed by Arkhangelsky et al. (2021). Vertical red line highlights the year of the price shock. Blue line represents the evolution of each outcome for treated municipalities. Red dashed line represents the evolution of each outcome for control municipalities.

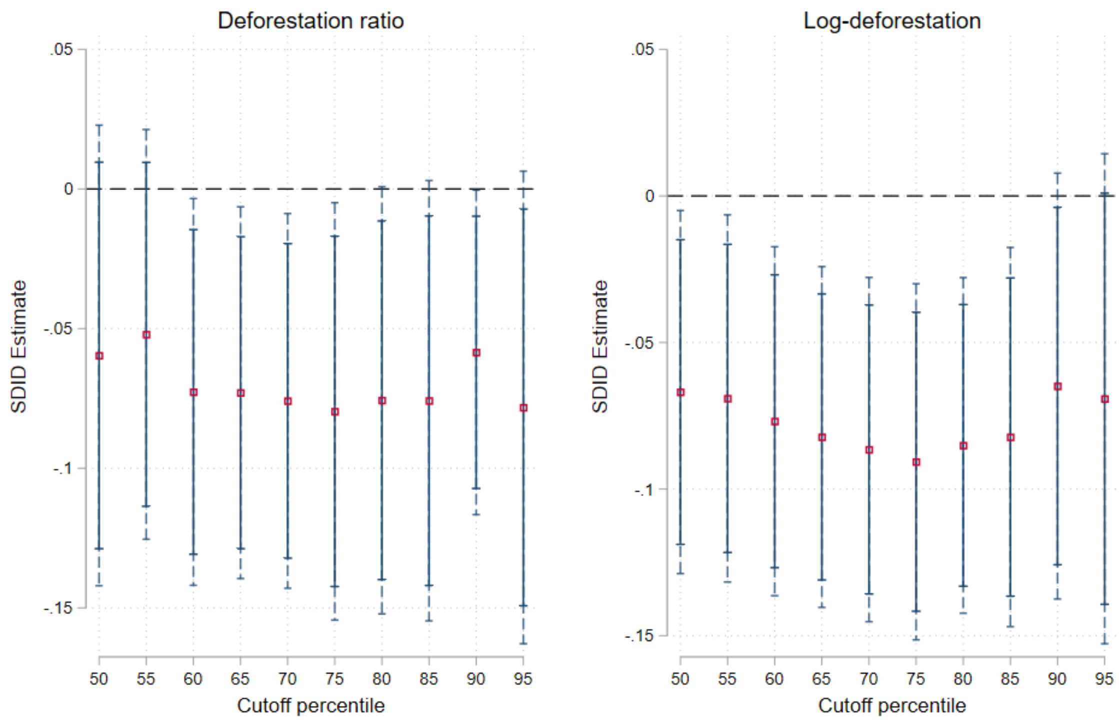
Figure 9: Deforestation series. Forest outside agricultural frontier.



(a) Deforestation ratio (b) Ha. deforested (log)

Notes: Each panel displays the corresponding series for control and treated municipalities as proposed by Arkhangelsky et al. (2021). Vertical red line highlights the year of the price shock. Blue line represents the evolution of each outcome for treated municipalities. Red dashed line represents the evolution of each outcome for control municipalities.

Figure 10: Effect of price shock on deforestation.Alternative cutoffs



Notes: This figure displays the point estimates for the main outcomes and their corresponding 90 and 95 percent confidence intervals in dashed and solid lines, respectively. Horizontal axis denotes the percentile above which treated units are defined.

Table 1: Crop selection

Crop	IFA category	Intensity (MT/Ha)
Cafe Tipica - Pajarito Café variedad Colombia Cafe Caturra Café Castilla	Coffee green	0.295
Algodón	Cottonseed	0.480
Mango Mandarina Mora Andina Banano tipo exportación Limón Naranja Chontaduro Aguacate Piña Banano Platano	Fruits, citrus, treenuts	0.177
Maíz Blanco Maíz Amarillo	Maize	0.130
Palma africana	Oil palm	0.279
Coco	Other oil crops	0.026
Fríjol	Pulses	0.129
Cacao grano	Residual	0.056
Arroz verde	Rice	0.157
Ahuyama Arracacha Ñame Papas Yuca	Roots/tubers	0.272
Caña de azúcar Caña panelera	Sugar cane	0.157

Notes: This table displays the fertilizer intensity for each of the crops used to calculate municipality-level fertilizer intensity. Each crop on CNA is assigned to each of the categories provided by International Fertilizer Association (IFA). Fertilizer intensity is calculated as required metric tons per crop hectare.

Table 2: Descriptive statistics of main variables

	Obs.	Mean	Std.Dev.	Min.	Max.
Panel A: Municipality- Year					
Ha. Deforested (log)	21,643	1.75	1.77	0.00	10.39
Deforestation (%)	21,643	0.18	0.49	0.00	22.94
Agricultural Frontier (%)	21,643	0.46	0.23	0.00	0.97
Panel B: Municipality					
Crop land (1000 Ha.)	941	30.20	94.65	0.01	1,780.50
Fertilizer Intensity	941	16.39	4.03	7.10	27.85
Forest percentage	941	23.22	24.55	0.04	98.69
Forest area (1000 Ha.)	941	72.89	428.41	0.01	8236.197
Inorganic fert. area (1000 Ha.)	941	5.41	13.23	0.00	229.09

Notes: This table presents descriptive statistics for main variables. Panel A shows the variables at the municipality-year level. Panel B displays the variables at the municipality level. All the variables are measured in 2014, except for forest variables which are measured in 2019.

Table 3: Main effect of price shock on deforestation

	Deforestation ratio	Ha. Deforested (log)
Panel A		
Treated x After 2021	-0.076	-0.086
	(0.039)*	(0.035)**
Department- time FE	NO	NO
Panel B		
Treated x After 2021	-0.066	-0.045
	(0.036)*	(0.034)
Department- time FE	YES	YES
N	21643	21643
Mean dep. var (Pre)	0.161	1.708
Mean dep. var (2020)	0.306	2.053

Notes: Standard errors are bootstrapped using 100 repetitions and clustered at the municipality level. Each specification includes municipality, year fixed effects. Panel B includes department-time fixed effects. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 4: Effect relative to agricultural frontier

	Agr. Front		Outside Agr. Front	
	Ratio	Hectares (log)	Ratio	Hectares (log)
Panel A				
Treated x After 2021	-0.050	-0.072	-0.011	-0.054
	(0.023)**	(0.025)***	(0.026)	(0.033)
Department-time FE	NO	NO	NO	NO
Panel B				
Treated x After 2021	-0.034	-0.049	-0.020	-0.025
	(0.016)**	(0.025)*	(0.025)	(0.030)
Department-time FE	YES	YES	YES	YES
N	21643	21643	21643	21643
Mean dep. var (Pre)	0.050	0.860	0.111	1.483
Mean dep. var (2020)	0.084	1.058	0.221	1.823

Notes: Standard errors are bootstrapped using 100 repetitions and clustered at the municipality level. Each specification includes municipality, year fixed effects. Panel B includes department-time fixed effects. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 5: Heterogeneous effects. All forest

	Z: Forest	Z: Road density	Z: Protected areas
Panel A: Deforestation ratio			
Treated x Post x Z	0.060	-0.027	0.112
	(0.051)	(0.059)	(0.061)*
Z x Post	-0.051	-0.054	-0.152
	(0.045)	(0.044)	(0.042)***
Treated x Post	-0.054	-0.048	-0.074
	(0.053)	(0.051)	(0.052)
$p - value$	0.663	0.216	0.286
Panel B: Log deforestation			
Treated x Post x Z	-0.211	0.244	0.017
	(0.060)***	(0.096)**	(0.074)
Z x Post	0.225	-0.212	-0.076
	(0.047)***	(0.046)***	(0.051)
Treated x Post	0.034	-0.005	-0.055
	(0.060)	(0.059)	(0.063)
$p - value$	0.634	0.826	0.342
N	21643	21643	21643
Mean dep. Var (Panel A)	0.180	0.180	0.180
Mean dep. Var (Panel B)	1.753	1.753	1.753

Notes: Standard errors are bootstrapped using 100 repetitions and clustered at the municipality level. Each specification includes municipality, year fixed effects. Panel A uses deforestation ratio as dependent variable, while panel B uses the log of hectares deforested. Each column represents a municipality characteristic dummy, denoted as Z, calculated before the shock. Column 1 represents a dummy indicating that the municipality is above the median of forest-area ratio. Column 2 represents a dummy indicating that the municipality is above the median of road density. Column 3 represents a dummy indicating that the municipality is above the median of protected forest area relative to entire forest. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 6: Heterogeneous effect inside agricultural frontier

	Z: Forest	Z: Road density	Z: Protected areas
Panel A: Deforestation ratio			
Treated x Post x Z	0.062	-0.040	-0.004
	(0.022)***	(0.035)	(0.028)
Z x Post	-0.038	-0.012	-0.028
	(0.017)**	(0.016)	(0.018)
Treated x Post	-0.005	0.004	-0.010
	(0.020)	(0.017)	(0.022)
$p-value$	0.646	0.264	0.356
Panel B: Log deforestation			
Treated x Post x Z	-0.065	0.065	-0.050
	(0.052)	(0.068)	(0.062)
Z x Post	0.058	-0.114	-0.017
	(0.034)*	(0.034)***	(0.036)
Treated x Post	0.031	0.025	0.009
	(0.054)	(0.053)	(0.055)
$p-value$	0.775	0.792	0.547
N	21643	21643	21643
Mean dep. Var (Panel A)	0.055	0.055	0.055
Mean dep. Var (Panel B)	0.883	0.883	0.883

Notes: Standard errors are bootstrapped using 100 repetitions and clustered at the municipality level. Each specification includes municipality, year fixed effects. Panel A uses deforestation ratios as dependent variable, while panel B uses the log hectares deforested. Each column represents a municipality characteristic dummy, denoted as Z, calculated before the shock . Column 1 represents a dummy indicating that the municipality is above the median of forest-area ratio. Column 2 represents a dummy indicating that the municipality is above the median of road density. Column 3 represents a dummy indicating that the municipality is above the median of protected forest area relative to entire forest. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Table 7: Heterogeneous effect outside agricultural frontier

	Z: Forest	Z: Road density	Z: Protected areas
Panel A: Deforestation ratio			
Treated x Post x Z	-0.003	0.035	0.120
	(0.040)	(0.051)	(0.050)**
Z x Post	-0.009	-0.048	-0.123
	(0.029)	(0.028)*	(0.031)***
Treated x Post	-0.006	-0.001	-0.064
	(0.032)	(0.029)	(0.038)*
$p-value$	0.783	0.840	0.408
Panel B: Log deforestation			
Treated x Post x Z	-0.230	0.272	0.021
	(0.083)***	(0.090)***	(0.071)
Z x Post	0.270	-0.223	-0.053
	(0.046)***	(0.046)***	(0.051)
Treated x Post	0.023	-0.025	-0.065
	(0.055)	(0.056)	(0.060)
$p-value$	0.574	0.833	0.403
N	21643	21643	21643
Mean dep. Var (Panel A)	0.124	0.124	0.124
Mean dep. Var (Panel B)	1.527	1.527	1.527

Notes: Standard errors are bootstrapped using 100 repetitions and clustered at the municipality level. Each specification includes municipality, year fixed effects. Panel A uses deforestation ratios as dependent variable, while panel B uses the log hectares deforested. Each column represents a municipality characteristic dummy, denoted as Z, calculated before the shock . Column 1 represents a dummy indicating that the municipality is above the median of forest-area ratio. Column 2 represents a dummy indicating that the municipality is above the median of road density. Column 3 represents a dummy indicating that the municipality is above the median of protected forest area relative to entire forest. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 8: Effect of price shock on deforestation. Standard DiD

	Deforestation ratio	Ha. Deforested (log)
Panel A		
Treated x After 2021	-0.043	-0.097
	(0.032)	(0.042)**
Department- time FE	NO	NO
Panel B		
Treated x After 2021	-0.057	-0.059
	(0.034)*	(0.042)
Department- time FE	YES	YES
N	21643	21643
Mean dep. var (Pre)	0.161	1.708
Mean dep. var (2020)	0.306	2.053

Municipality clustered standard errors are presented in parenthesis. Each specification includes municipality, year fixed effects. Panel B includes department-time fixed effects. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 9: Effect of price shock on deforestation. Removing extreme values of forest cover

	Agr. Front		Outside Agr. Front	
	Ratio	Hectares (log)	Ratio	Hectares (log)
Panel A: Removing below 10th				
Treated x After 2021	-0.032	-0.077	-0.008	-0.067
	(0.012)***	(0.026)***	(0.012)	(0.035)*
N	19481	19481	19481	19481
Panel B: Removing above 90th				
Treated x After 2021	-0.042	-0.063	-0.015	-0.027
	(0.018)**	(0.021)***	(0.024)	(0.035)
N	19481	19481	19481	19481
Panel C: Removing both				
Treated x After 2021	-0.031	-0.067	-0.013	-0.038
	(0.013)**	(0.026)**	(0.014)	(0.037)
N	17319	17319	17319	17319
Mean dep. var (Pre)	0.050	0.860	0.111	1.483
Mean dep. var (2020)	0.084	1.058	0.221	1.823

Municipality clustered standard errors are presented in parenthesis. Each specification includes municipality and year fixed effects. Excludes municipalities below the 10th and above the 90th percentile of forest cover. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$