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International Trade and Land-Use Change

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Abstract This paper measures the environmental footprint of trade-related activities that use land intensively. By combining detailed data on forest cover at the municipal level in Colombia with exports at the same level of disaggregation, the study measures the extent to which the exports of agriculture, mining, and livestock are associated with deforestation. It establishes a causal link by relying on a measure of foreign demand as a source of exogenous variation for the export variable. While exports in some sectors have led to deforestation, this effect is mitigated when production is located in protected areas, indicating that there is no linear relationship between agricultural exports and deforestation. This, in turn, suggests several areas for public policy intervention.

Keywords: Exports, Deforestation, Climate Change, Emissions

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I. Introduction

According to the United Nations, climate change threatens the lives and livelihoods of billions of people through natural disasters, environmental degradation, and extreme weather patterns (UN, 2017). The consequences of climate change, including extreme weather events, sea-level rise, and disruptions to ecosystems, have the potential to harm economies, food security, and public health on a global scale.

Designing policies to adequately mitigate climate change requires first measuring the environmental footprint of its sources. By understanding which sectors or activities are the largest emitters, policymakers can prioritize their efforts and implement targeted measures to address these sources.

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A growing body of empirical analyses is dedicated to measuring the contribution of international trade to climate change (for a review, see Copeland et al., 2021). Most of this literature focuses on measuring the greenhouse gas (GHG) emissions associated with the production and transportation of internationally traded goods. However, the majority of this work does not examine the environmental impacts that may occur through trade-related changes in land use.[1] Land-use changes from activities such as agriculture, mining, and livestock could lead to losses of forest cover, with significant consequences for climate change. Therefore, assessing the role that trade may have in forest cover losses requires measuring the extent to which these changes occur in response to foreign demand. In other words, it is essential to measure the environmental footprint of trade-related activities that use land intensively.

The objective of this paper is to employ specialized data to measure the impact of international trade on deforestation in Colombia. The focus is on sectors most associated with land use: agriculture, mining, and livestock. Colombia is one of the countries with the greatest biodiversity in the world, featuring a wide range of ecosystems, including tropical rainforests and cloud forests. This offers an ideal setting for the task at hand.

Theoretically, the production of agricultural products for export can lead to direct deforestation when forests are cleared to make way for farmland or to expand existing agricultural operations. For example, when forests in tropical regions are cleared to make room for crops like soy, palm oil, and beef, which are often exported to international markets, deforestation can increase. As global demand for agricultural products increases, it can put pressure on local farmers and producers to increase their yields, which can lead to the expansion of agricultural land into forested areas.

But the increase in exports may occur on land that was previously used for farming, rather than on forested land. This means that deforestation is not necessary to expand agricultural production. Also, more exports can be the result of an intensification of production, for instance through improvements in technology, that did not require new land and therefore had no effect on deforestation. Agricultural producers and exporters can adopt sustainable farming practices that minimize or eliminate deforestation. This includes techniques like agroforestry, where crops and trees are grown together, reducing the need to clear forests. Sustainable agriculture practices can be employed to maximize yields while minimizing environmental impact.

Consequently, the extent to which exports lead to more deforestation is an empirical question. In a world increasingly concerned about climate change and increasingly willing to consider trade-related measures to address it, it is of utmost importance to carefully measure the extent

1) Most analyses measuring the production-side-emissions related to international trade rely on some type of environmentally extended input-output matrix, such as the World Input-Output Dataset (WIOD) or the Global Trade Analysis Project (GTAP). However, one limitation of these matrices is that they generally lack information on land use. Consequently, the production of traded goods that potentially generates GHG through its impacts on deforestation can hardly be captured by these matrices.

to which deforestation is associated with trade flows of goods that are intensive in land use.

Combining very detailed data on forest cover at the municipal level in Colombia and exports at the same level of disaggregation, we measure the extent to which the exports of agriculture, mining and livestock are associated with deforestation during the 2010-2020 period. To establish a causal link between exports and forest cover we construct a measure of foreign demand for agricultural, mining and livestock products and use it as a source of exogenous variation for the export variable.

We also examine whether protected natural areas in Colombia are associated with less deforestation and, importantly, whether the export-associated production that can be legally located within these areas has an attenuated impact on deforestation.

We bring robustness into the analysis by employing alternative datasets of forest cover as well as by conducting a number of robustness checks to the estimations.

Our study is part of a growing body of analyses linking globalization and deforestation. Some of this work has been based on cross-country regressions to examine, among other factors, the impact of a variety of aspects related to globalization (for example, exports, terms of trade, regional trade agreements, real exchange rate) on deforestation (Barbier and Burgess, 2001; Barbier, 2004; Barbier et al., 2005; Arcand et al., 2008; Damette and Delacote, 2011; Leblois et al., 2017; Abman and Lundberg, 2020). A very small parallel line of work is country-specific and seeks to exploit variation between political subdivisions within a country to identify the associated effects (Faria and Almeida, 2016; Carreira et al., 2022). These analyses, including our study, combine high-resolution maps of forest cover with detailed measures of international trade at the municipality level to estimate the footprint of international trade through its impact on deforestation.

Focused on the agricultural sector, for example, Carreira et al. (2022) found no significant impact of trade on deforestation in Brazil. The authors also examine the role of genetically engineered (GE) soybean seeds on deforestation. They found that the introduction of these seeds induced deforestation, as GE soybean seeds allowed the expansion of soy production to areas that were not commercially viable using traditional soy seeds. The analysis in Faria and Almeida (2016) is also focused on Brazil. The main results of this work suggest that openness to trade in the Brazilian Amazon increased deforestation.

Our study complements these analyses by examining another country, Colombia. The contribution of this paper to the literature is twofold. First, we explicitly study the role of exports not only from the agricultural sector, as in Carreira et al. (2022), but also from mining and livestock. Therefore, we expand the sectoral coverage of trade-related activities that use land intensively and measure their impact on deforestation. Second, we examine the extent to which the potential impacts of trade on deforestation differ in areas of the country that are considered protected. This is the first study that incorporates the role of protected areas when analyzing trade and land use.

Our study is relevant not only for Colombia, but also for many other countries in South America, Africa, and Asia where there are agricultural, mining, or livestock activities, as well as a significant presence of forests. The study is also pertinent for many countries that use protected areas to pursue conservation objectives.

We find evidence that agricultural exports are associated with deforestation. In particular, other things equal, municipalities with 10% more agricultural exports are associated with 0.3% less forest cover area. The estimations imply that the average growth of agricultural exports during the period analyzed is associated with an annual reduction of 41 thousand hectares of forest cover, equivalent to 25% of the average annual deforestation in the country. Such change in forest cover is associated with roughly 4.9 million tons of carbon emissions per year. In livestock, the evidence is much weaker because the estimates are only statistically significant in the regressions that employ one of the forest datasets that we have assembled. We did not find an association between the exports of mining products and forest cover during the period of analysis. Our results also show that the export impact on deforestation is ameliorated when the production associated with these exports is located in areas of the country that have been designated as protected.

The rest of the article is organized as follows. Section 2 presents the empirical strategy and describes the various databases employed. Section 3 discusses the results of the econometric estimations. Finally, section 4 provides concluding remarks.

II. Empirical Strategy

Econometrically estimating the effect of agricultural exports on deforestation involves designing a research methodology that considers various economic, environmental, and social factors. Our empirical strategy relies on the following baseline equation:

$$\ln F_{it} = \beta \cdot lnE_{it} + \overline{Z}_{it} \cdot \gamma + \theta_i + \theta_t + \epsilon_{it} \tag{1}$$

where $\ln F_{it}$ is the log of the forest area (measured in hectares) in municipality i in year t; $\ln E_{it}$ is the log of exports (of agriculture, mining, and livestock) from municipality i in year t; $\overline{Z}_{it}$ is a vector of time-variant municipality controls including coca cultivation, population, income per capita and precipitation levels; θ_i and θ_t are municipality and year fixed effects, respectively. Finally, ϵ_{it} is the error term. The time period of the analysis is 2010-2020.

One limitation with equation (1) is that there could be factors influencing forest cover and

Colombian production (and exports) at the same time. Accordingly, we cannot simply imply causality from exports to forest cover.

We deal with this issue in two ways. First, we control directly for many factors at the local level that may have affected land use in Colombia. This is the role of the $\overline{Z}_{it}$ vector in equation (1). For example, a potentially important factor in Colombia is drug-related plantations. The Colombian government estimates that 22% of deforestation occurring in the country is a result of coca cultivation. Much of this forest clearance occurs in areas of high biodiversity, with the slash-and-burn technique increasing soil erosion, and the use of herbicides. For example, a number of studies have found a positive association between coca plantations and deforestation (Dávalos et al., 2011; Armenteras et al., 2013; Negret et al., 2019). Regions where illicit crops and deforestation coincide also tend to exhibit high levels of violence (Bonilla-Mejía and Higuera-Mendieta, 2019; Fergusson et al., 2014). Consequently, we directly include a variable that captures coca crops, in particular, the share of the municipality area with coca plantations. This variable is available at the municipality-year level.

We also control for additional factors, namely population (to control for municipality size), income per capita (to control for the level of development) and precipitation levels. These variables are also available at the municipality-year level. We also include a variable that captures the share of the municipality that falls into what is called a protected natural area. These are areas aimed at contributing to the country's conservation strategies. The total size of these areas has been growing steadily and currently covers approximately 160,000 square km, or 14% of the country's total land area. Because the municipality forest area in period t is positively correlated with the forest area in previous periods, we also include as an additional regressor the initial forest area of the municipality in year 2010 multiplied by a time-trend. This allows for differential trends for municipalities with different initial characteristics in terms of forest area. Finally, we also include municipality fixed effects in the regressions to account for time-invariant local factors.

The second way we deal with endogeneity is to employ an instrumental variable estimation. We construct a measure of foreign demand for agricultural, mining and livestock products and use it as a source of exogenous variation for the export variable. In particular, the instrument is based on the following equation:

$$IV_{it} = \Sigma_k \frac{X_{ikt_0}}{X_{kt_0}} \cdot M_{kt} \tag{2}$$

where M_{kt} is the world's imports of product k in year t (excluding the exports of Colombia to the world); and X_{ikt_0}/X_{kt_0} is the share of municipality i in Colombia's total production of good k in year 2007.[2] IV_{it} measures the municipality exposure to foreign demand of agricultural, mining and livestock products, where the exposure is based on pre-analysis participation of the locality in Colombia's total production of good k.

Note that the instrument uses foreign demand of agricultural, mining and livestock products, which is then apportioned at the local level according to the participation of the municipalities in a time preceding the analysis. This purges the instrument of possible confounding factors that could arise if contemporaneous participation shares are used. The intuition behind the instrument is that β will be estimated using variation in the exports of agricultural, mining and livestock products that arise only from exogenous foreign demand for these products and not from other factors that could simultaneously affect exports and forest cover at the same time.

A. Data description

We use administrative records of all export transactions between 2010 and 2020 from the Colombian Statistics Office (*Departamento Administrativo Nacional de Estadística*, DANE). The database contains information about the origin of the exports at the state level (in Colombia this is called Department). We complement this information with official data on production of agriculture, mining and livestock at the state and municipal level.[3] We assign state exports to municipalities according to their participation in state production. We do this for each product in the agriculture, mining and livestock sectors.

The data on forest cover is from the Institute of Hydrology, Meteorology, and Environmental Studies of Colombia (IDEAM).[4] To track changes in land use and forest areas over time, IDEAM collects the data from various sources, such as satellite imagery, remote sensing technology, and ground-based observations.[5] We collect different blocks of information from IDEAM, some consist of information on forest cover and others on deforestation. We assemble all these blocks to obtain a consistent and unified series of forest cover between the years 2010 and 2020.

To bring robustness into the analysis, we employ a second dataset of forest cover from the Global Forest Change (GFC) which is based on satellite imagery (Hansen et al., 2013). Figure 1 compares the implied level of accumulated deforestation (from 2010 to 2020) at the municipality level between the IDEAM and GFC datasets. The correlation between the two

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2) Data availability precludes us to use an earlier year.

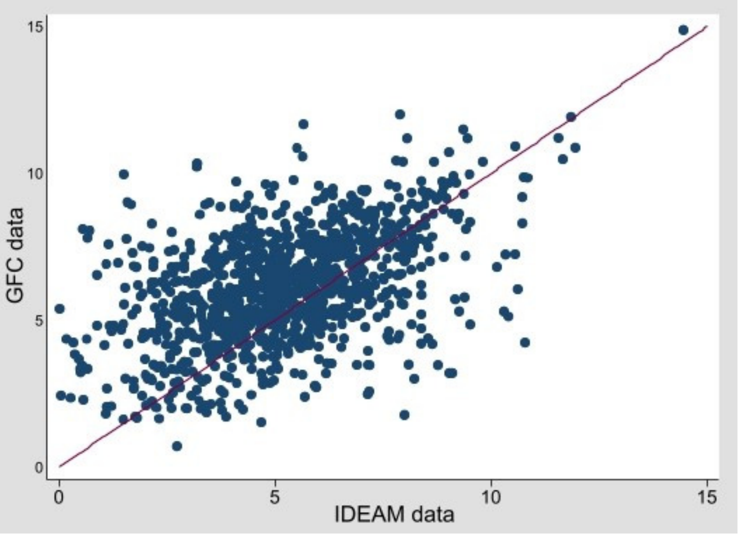
3) These datasets are from the Ministry of Agriculture and Rural Development, and the Ministry of Mines and Energy.

4) IDEAM's role in monitoring deforestation includes data collection and analysis, policy support and public awareness.

5) Forest was defined as land with a minimum tree canopy density of 30% and a minimum height of canopy of 5 m at the time of its identification.

series is 0.486. Note that, in general, there are many more points above than below the 45-degree line. This means that, relative to the IDEAM data, deforestation implied by the GFC tends to be higher.

Figure 1. Accumulated deforestation between 2010 and 2020 according to GFC and IDEAM, in logs



Our data on coca plantations come from the Integrated Monitoring System of Illicit Crops (SIMCI) of the United Nations Office on Drugs and Crime (UNODC). This measure is based on satellite imagery. We use this information to calculate the share of coca plantations in the total area of the municipality.

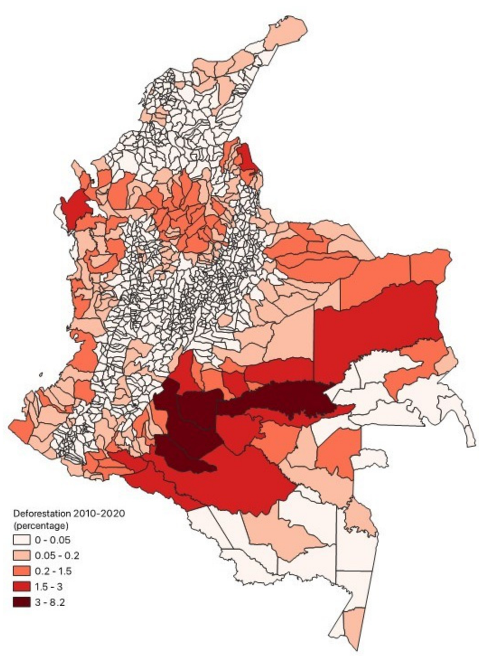
We employ geographical information system (GIS) data on the boundaries of the Natural Protected Areas to calculate the share of protected areas in the total area of the municipality. The GIS data come from the National Register of Protected Areas (RUNAP).

Our data on population and income per capita at the municipality level come from DANE. Finally, the annual precipitation data come from IDEAM. Table A1 in the online Appendix summarizes all the variables and data sources.

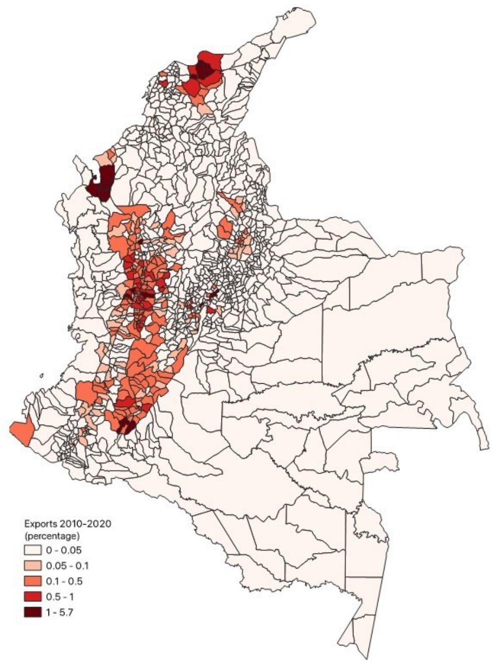
Panel A of Figure 2 presents a map that helps to visualize which are the municipalities that have experienced the highest levels of deforestation during the period analyzed.[6] The map can be thought of as the differences in two forest cover maps, one at the beginning and one at the end of the period. According to IDEAM, accumulated deforestation in Colombia between 2010 and 2020 amounts to 1.6 million hectares, or 160,000 hectares on average per year.

6) The map is based on data from IDEAM.

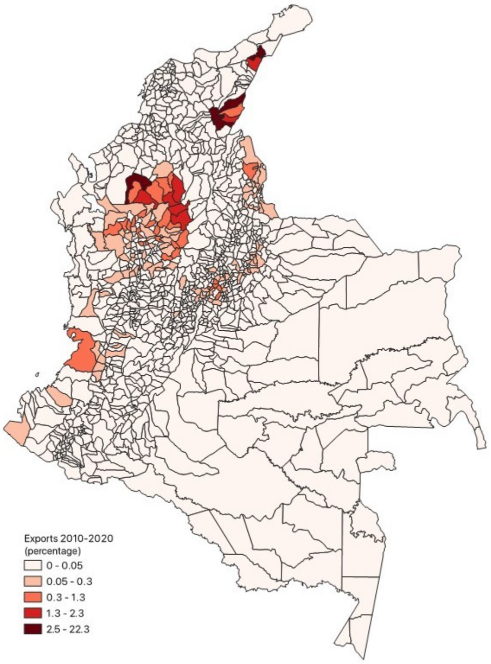
Figure 2. Share of municipality in Colombian deforestation and exports



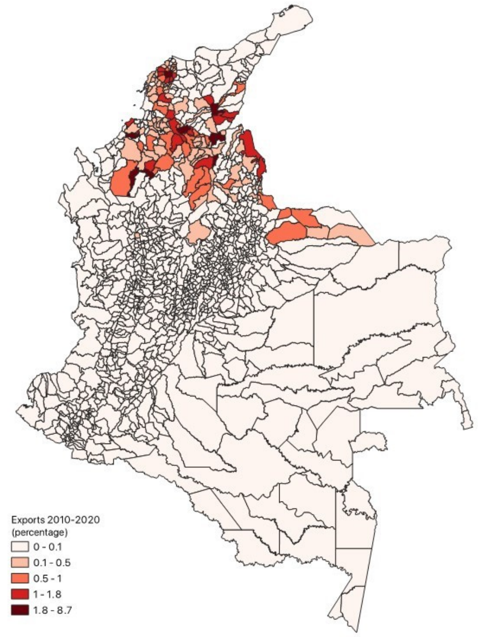
Panel A: Deforestation



Panel B: Agricultural exports



Panel C: Mining exports

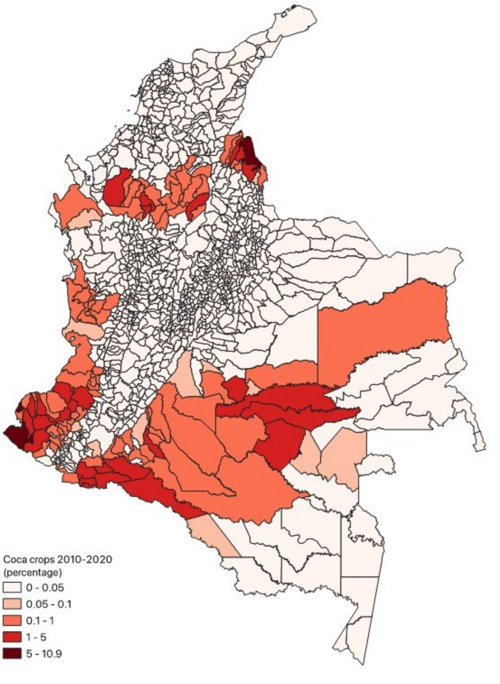


Panel D: Livestock exports

Panels B, C, and D of Figure 2 present the accumulated exports of agriculture, mining, and livestock, respectively. Whether municipalities with higher exports are associated with higher use of forest land, and therefore higher deforestation, is not obvious at first glance.

For its part, Figure 3 shows the share of coca plantations by municipality. Visually, there is a relationship between coca plantations and deforestation. In the next section, we use econometric analysis to measure the relationship between exports and forest cover, controlling for coca plantations and the other covariates.

Figure 3. Share of municipality in Colombian coca plantations



III. Econometric Results

In this section we first present the results of the OLS regressions, including the comparison when the two databases of forest cover are employed. These regressions do not provide a notion of causality but provide basic insights about the level and direction of correlations. Next, we will examine the results that imply causality when we run the 2SLS regressions. A battery of robustness tests is also applied to these regressions. Finally, we present regressions where the role of protected areas and their interaction with exports is analyzed.

Table 1 shows OLS estimates of equation (1). The dependent variable of interest is the municipality's total exports of agricultural, mining and livestock products. Covariates are added progressively in columns 2 and 3. Note that none of the coefficients of the export variable is statistically significant, which may be the result of the three sectors being added. It is worth highlighting the negative coefficient for coca plantations, corroborating the notion that a greater extension of coca crops is associated with a reduction in forest area.

Table 1. *OLS Estimations*

	(1)	(2)	(3)
Ln exp (agr+min+liv)	0.0003	0.0002	0.0003
	(0.0005)	(0.0005)	(0.0005)
Ln coca plantation		-0.0031**	-0.0030**
		(0.0014)	(0.0014)
Ln population		-0.0024	-0.0021
		(0.0065)	(0.0065)
Ln income		0.0044	0.0041
		(0.0030)	(0.0030)
Precipitation		0.0125***	0.0125***
		(0.0026)	(0.0027)
Forest area 2010 x trend		0.0022***	0.0022***
		(0.0002)	(0.0002)
Share of protected area			0.0391***
			(0.0081)
R2	0.998	0.999	0.999
Observations	11,744	11,714	11,714

Notes. Each column reports results from regressions over the period 2010-2020. The dependent variable is the area of forest cover in the municipality, measured in hectares (in logs). The explanatory variables are the municipality total exports of agricultural, mining and livestock products (in logs), the area of coca plantation (in logs), the total population in the municipality (in logs), the average income per capita of the municipality (in logs), a dummy variable equal to 1 if the precipitation in the municipality is above the median of the country and 0 otherwise, the initial area of forest cover (in 2010) multiplied by a time trend, and the share of the municipality area that falls under the category of a natural protected area. Additional controls are municipality and year fixed effects. Robust standard errors in parentheses are clustered at the municipality level.
*** ; ** ; * significant at the 1%, 5% and 10% level respectively.

To explore whether there is a correlation between forest cover and the exports of specific sectors, Table 2 separates the municipality's exports by agriculture, mining, and livestock. Importantly, all the regressions include the same covariates as in Table 1. As mentioned in section 2.1, we employ two alternative datasets of forest cover. In particular, all the regressions in Panel A use forest cover data from IDEAM, while all the regressions in Panel B use forest cover data from GPC.

Table 2. *OLS Estimations by Sectors*

Panel A: IDEAM	(1)	(2)	(3)	(4)
Ln exp (agr)	-0.0001**			-0.0001**
	(0.0004)			(0.0004)
Ln exp (min)		-0.0001		-0.0001
		(0.0002)		(0.0002)
Ln exp (liv)			0.0001	0.0001
			(0.0003)	(0.0003)
R2	0.999	0.999	0.999	0.999
Observations	11,744	11,714	11,714	11,714
Panel B: GFC				
Ln exp (agr)	-0.0005***			-0.0006***
	(0.0001)			(0.0001)
Ln exp (min)		0.0001		0.0001
		(0.0001)		(0.0001)
Ln exp (liv)			-0.0004***	-0.0004***
			(0.0001)	(0.0001)
R2	0.999	0.999	0.999	0.999
Observations	11,744	11,714	11,714	11,714

Notes. Each column reports results from regressions over the period 2010-2020. In panel A, forest cover is measured with data from IDEAM, while in panel B, forest cover is measured with data from the Global Forest Change (GFC). The dependent variable is the area of forest cover in the municipality, measured in hectares (in logs). The explanatory variables are the municipality total exports of agricultural products (columns 1 and 4), mining products (columns 2 and 4), and livestock products (columns 3 and 4), (in logs); the area of coca plantation (in logs); the total population in the municipality (in logs); the average income per capita of the municipality (in logs); a dummy variable equal to 1 if the precipitation in the municipality is above the median of the country and 0 otherwise, the initial area of forest cover (in 2010) multiplied by a time trend, and the share of the municipality area that falls under the category of a natural protected area (sum of local, regional and national areas). Additional controls are municipality and year fixed effects. Robust standard errors in parentheses are clustered at the municipality level.
*** ; ** ; * significant at the 1%, 5% and 10% level respectively

The results in Panel A show that the coefficient for agriculture is negative and significant at 5%, implying that more exports in agriculture are associated with less forest cover. The coefficients for the other sectors are not statistically significant. In Panel B, agricultural exports are also found to be negatively correlated with forest cover. In this panel, the exports of livestock are also found to be negatively correlated with forest cover.

Table 3 turns to causal relationships by presenting the estimates from the 2SLS regressions. The results from Panel A confirm the preliminary findings from the OLS regressions in Table 2 (Panel A) of a negative and significant relationship between exports and forest cover in the agricultural sector. The absolute value of the estimated coefficient is much larger than the OLS coefficient, suggesting a downward bias in the OLS estimation. The results from Panel B of Table 3 also confirm the preliminary findings from the OLS regressions in Table 2 (Panel B) of a negative and significant relationship between exports and forest cover in both the agricultural and livestock sectors.

Table 3. *2SLS Estimations*

Panel A: IDEAM	(1)	(2)	(3)
	Agriculture	Mining	Livestock
Ln exp	-0.0321**	0.0141	-0.0186
	(0.0101)	(0.0165)	(0.0117)
R2	0.999	0.999	0.999
Observations	11,744	11,714	11,714
F statistic	19.1	5.4	8.7
Panel B: GFC			
Ln exp	-0.0138***	0.0018	-0.0126***
	(0.0039)	(0.0019)	(0.0044)
R2	0.999	0.999	0.999
Observations	11,744	11,714	11,714
F statistic	19.4	6.1	9.5

Notes. Each column reports results from regressions over the period 2010-2020. In panel A, forest cover is measured with data from IDEAM, while in panel B, forest cover is measured with data from the Global Forest Change (GFC). The dependent variable is the area of forest cover in the municipality, measured in hectares (in logs). The explanatory variables are the municipality total exports of agricultural products (column 1), mining products (column 2), and livestock products (column 3), (in logs), the area of coca plantation (in logs), the total population in the municipality (in logs), the average income per capita of the municipality (in logs), a dummy variable equal to 1 if the precipitation in the municipality is above the median of the country and 0 otherwise, the initial area of forest cover (in 2010) multiplied by a time trend, and the share of the municipality area that falls under the category of a natural protected area. Additional controls are municipality and year fixed effects. Robust standard errors in parentheses are clustered at the municipality level.

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

As noted before, the regressions with the GFC dataset have been added as a robustness exercise; consequently, the results of Panels A and B, taken together, can be read as strong evidence of a negative relationship between exports and forest cover in the case of agriculture (since the result is valid regardless of the forest cover dataset used), and weak evidence in the case of livestock (since this result is only significant in one of the forest datasets employed).

In Table 4 we conduct additional robustness tests by dropping outlier observations and rerunning the regressions. In particular we drop observations below the 1st percentile and above the 99th percentile of a variable's distribution. We do this for the forest cover variable (columns 1-3), the exports variable (columns 4-6), and both variables at the same time (columns 7-9). Qualitatively, the results in Panels A and B do not change in any significant way in relation to those of Table 3.

Table 4. *2SLS Estimations. Robustness Regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Drop outliers in forest cover			Drop outliers in exports			Drop outliers in forest cover and exports		
Panel A: IDEAM	Agriculture	Mining	Livestock	Agriculture	Mining	Livestock	Agriculture	Mining	Livestock
Lnexp	-0.0197*** (0.0070)	0.0139 (0.0160)	-0.0129 (0.0089)	-0.0341*** (0.0108)	0.0064 (0.0058)	-0.0198 (0.0123)	-0.0212*** (0.0075)	0.0067 (0.0046)	-0.0135 (0.0092)
R2	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
Observations	11,533	11,533	11,533	11,590	11,589	11,604	11,409	11,408	11,425
F-statistic	19.7	5.5	9.5	18.2	4.9	8.6	18.8	5.1	9.7
Panel B: GFC									
Lnexp	-0.0128*** (0.0035)	0.0006 (0.0017)	-0.0091*** (0.0035)	-0.0142*** (0.0041)	-0.0012 (0.0017)	-0.0132*** (0.0048)	-0.0131*** (0.0037)	-0.0019 (0.0017)	-0.0091** (0.0036)
R2	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
Observations	11,533	11,533	11,533	11,590	11,589	11,604	11,409	11,408	11,425
F-statistic	18.5	6.6	8.4	18.5	5.5	8.7	17.7	5.9	8.0

Notes. Each column reports results from regressions over the period 2010-2020. In panel A, forest cover is measured with data from IDEAM, while in panel B, forest cover is measured with data from the Global Forest Change (GFC). Regressions in columns 1-3 drop observations below the 1 pct and above the 99 pct in terms of forest cover; regressions in columns 4-6 drop observations below the 1 pct and above the 99 pct in terms of exports; regressions in columns 7-9 drop observations below the 1pct and above the 99 pct in terms of forest cover and in terms of exports. The dependent variable is the area of forest cover in the municipality, measured in hectares (in logs). The explanatory variables are the municipality total exports of agricultural products (columns 1, 4 and 7), mining products (columns 2, 5 and 8), and livestock products (columns 3, 6 and 9), (in logs); the area of coca plantation (in logs); the total population in the municipality (in logs); the average income per capita of the municipality (in logs); a dummy variable equal to 1 if the precipitation in the municipality is above the median of the country and 0 otherwise, the initial area of forest cover (in 2010) multiplied by a time trend, and the share of the municipality area that falls under the category of a natural protected area (sum of local, regional and national areas). Additional controls are municipality and year fixed effects. Robust standard errors in parentheses are clustered at the municipality level
***; **; * significant at the 1%, 5% and 10% level respectively.

Going back to Table 3, we can use the results from the regressions to make a back-of-the envelope calculation of the deforestation-related GHG emissions associated with the exports. In the case of agricultural exports, the coefficient of Panel A is equal to -0.0321. This means that, other things equal, municipalities with 10% more agricultural exports are associated with 0.321% less forest cover area. In Colombia, agricultural exports grew, on average, by 2.26% per year between 2010 and 2020. Moreover, during this period, the average total forest area in the country was 56.5 million hectares. Accordingly, the estimated coefficient implies that the average growth of agricultural exports during the 2010-2020 period is associated with an annual reduction of forest cover of around 40.9 thousand hectares.[7] This is equivalent to 25% of the country's average annual deforestation. Carbon values of the Amazon forests are estimated at around 120 tons of carbon per hectare (Asner, 2012; Saatchi et al., 2007). Consequently, the annual reduction in forest cover induced by agricultural exports is associated with around 4.9 million tons of carbon emissions per year.[8] If we employ the coefficient estimate for agriculture exports in Panel B, the associated emissions are around 2 million tons of carbon.[9]

7) 0.0321 x 0.0226 x 56,457,102 = 40,957
8) 40,957 x 120 = 4,914,840

While the evidence for livestock is weaker, we can still calculate GHG implied emissions using the coefficient estimate in column 3 of Panel B (Table 3). During the 2010-2020 period, the average annual growth rate of livestock exports was 2.06%, after excluding outlier years. Thus, this growth was associated with an annual reduction in forest cover of around 14.7 thousand hectares, which implies around 1.8 million tons of carbon in emissions per year.[10]

A. Interaction with natural protected areas

As mentioned above, in Colombia there are natural protected areas in different parts of the country that aim to contribute to the country's conservation objectives. Colombia's intentions of establishing national parks and protected areas involve efforts to balance conservation with various economic, political, and social challenges. The history of protected areas in Colombia can be traced back to the early 20th century with the establishment of the country's first national park in 1970.

Currently, with a combined surface area of 160,000 square km, the extension of these areas has been increasing steadily and is expected to continue growing given the commitments assumed by Colombia at the Paris Climate Summit. The protected natural areas are divided into three classes: national, regional, and local. Land in national protected areas can only be used for conservation, education, and research. However, in regional and local protected areas, activities such as agriculture, mining and livestock are allowed as long as they are sustainable. This raises the question of whether production associated with exports located in regional and local areas has less of an impact on deforestation relative to exports emanating outside these areas.

To answer this question, we introduce interaction terms between the export variable and the municipality's share in regional and local areas in equation (1). We also include the shares of local, regional, and national protected areas separately in the regressions.

Figure 4 shows the evolution in the number of regional and local areas between 2010 and 2020 (Panel A) and in the extension that they cover (Panel B). While the number of local areas is much larger than the number of regional areas, the local areas are much smaller in comparison. Therefore, the surface of land covered by regional areas is much larger relative to that of local areas.

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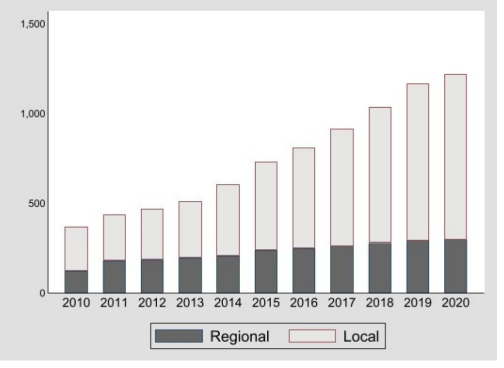
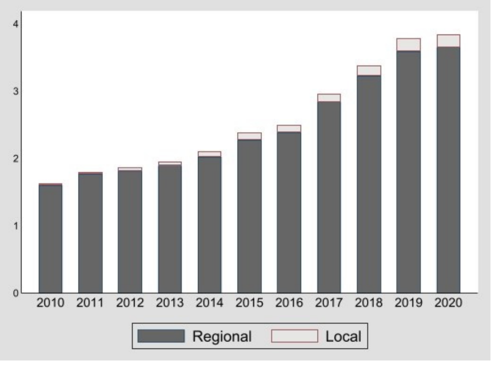
9) 0.0138 x 0.0226 x 56,457,102 x 120 = 2,112,940

10) 0.0126 x 0.0206 x 56,457,102 x 120 = 1,758,481

Figure 4. Regional and local natural protected areas



Panel A: Number of areas



Panel B: Extension of areas (millions of hectares)

Table 5 shows the results when the interaction terms are included in the regressions. The first row of Panel A confirms or previous results that only agricultural exports are negatively associated with forest cover when using the IDEAM database. Focused on column 1 of this panel, the interaction term between the export variable and the share of local protected area is positive and significant at the 1%, while the interaction with the regional area is not statistically significant. This result is confirmed in Panel B, where we use the GFC database: the interaction term is positive and significant for local areas and not significant for regional areas. Taken together, the results from the two panels suggest that the negative impact of agricultural exports on forest cover is lessened when the production of the associated exports takes place in local protected areas.

We can calculate how much the impact is lessened. Note that the average share of local protected areas among all municipalities is 0.145%. Accordingly, the impact of agricultural exports from local protected areas on forest cover -evaluated at the mean share of local areas- is equal to -0.0216.[11)] This implies that the negative impact of agricultural exports on forest cover in attenuated by around 1% when the production takes place in local protected areas.[12)]

The fact that we did not find an effect for the interaction term with respect to regional areas and that the positive effect for local areas is relatively small may be puzzling. After all, economic activities in these protected areas are allowed as long as they are compatible with the environment. If anything, it would be expected that exports emanating from these areas would not have any negative impact on forest cover. This is not what we found. The results indicate that the negative impact was effectively attenuated in local protected areas but there was still a negative impact; and in the case of regional areas, there was no attenuation.

11) -0.0218 + 0.00145 x 0.1154 = -0.0216

12) ((0.0216/0.0218)-1) x 100 = -0.92%

A potential explanation for these results is that we do not observe the precise location of the production activity associated with exports within the municipality. Our data contain information about the municipality of exports but does not have information about the precise location within the municipality. Therefore, it is not possible to know for sure that the export activity that takes place in a municipality with a protected area is located precisely within that protected area. Note that the greater the share of the protected area in the municipality, the greater the likelihood that the production activity behind the exports is located within that area. But in general, there could be production sites associated with the exports that are located outside the boundaries of the protected areas. This may explain the lack of larger positive results with respect to the interaction terms.

Table 5. *2SLS Estimations. Interactions with Protected Areas*

Panel A: IDEAM	(1)	(2)	(3)
	Agriculture	Mining	Livestock
Ln exp	-0.0218***	-0.0405	-0.0209
	(0.0082)	(0.7877)	(0.0216)
x Share of protected area local	0.1154***	0.4181	-0.2439
	(0.0425)	(7.4558)	(1.7668)
x Share of protected area regional	-0.0088	0.0003	0.1072
	(0.0056)	(0.0486)	(0.1101)
R2	0.999	0.999	0.999
Observations	11,744	11,714	11,714
Panel B: GFC			
Ln exp	-0.0148***	-0.0129	-0.0147***
	(0.0036)	(0.2496)	(0.0053)
x Share of protected area local	0.0840***	1.1013	-0.2346
	(0.0287)	(1.6416)	(1.0591)
x Share of protected area regional	0.0017	0.0001	0.0927
	(0.0035)	(0.0081)	(0.0759)
R2	0.999	0.999	0.999
Observations	11,744	11,714	11,714

Notes. Each column reports results from regressions over the period 2010-2020. In panel A, forest cover is measured with data from IDEAM, while in panel B, forest cover is measured with data from the Global Forest Change (GFC). The dependent variable is the area of forest cover in the municipality, measured in hectares (in logs). The explanatory variables are the municipality total exports of agricultural products (column 1), mining products (column 2), and livestock products (column 3), (in logs); the interactions of the export variable with the share of the municipality area that falls under the category of natural protected area, both for local and for regional; the area of coca plantation (in logs); the total population in the municipality (in logs); the average income per capita of the municipality (in logs); a dummy variable equal to 1 if the precipitation in the municipality is above the median of the country and 0 otherwise, the initial area of forest cover (in 2010) multiplied by a time trend, and the shares of the municipality area that falls under the categories of local, regional and national protected areas. Additional controls are municipality and year fixed effects. Robust standard errors in parentheses are clustered at the municipality level.

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Having found evidence of an attenuated effect through the interaction term, albeit small, is consistent with the notion that there is not necessarily a linear relationship between higher exports and higher deforestation, and that it all depends on the extent to which the growth of exports is based on the expansion of land used versus an increase in the intensity of production. For example, if the increase in exports occurs mainly through the intensification of production, for instance through improvements in technology that make production more compatible with the environment, the impact on the forest would be much less.

IV. Concluding Remarks

A large body of literature on the relationship between trade and the environment has emerged in the last two decades. Part of this literature focuses on the effects of trade on the environment due to the carbon emissions generated by the production and transportation of goods that cross borders. However, little attention has been devoted to measuring the environmental impacts that may occur through trade-related changes in land use. This study is part of a small but growing body of analyses that measure the environmental footprint of trade-related activities that use land intensively.

We examine the case of Colombia, one of the countries with the greatest biodiversity in the world. Combining detailed data on forest cover at the municipal level and exports at the same level of disaggregation, we take a close look at the sectors most associated with land use: agriculture, mining, and livestock. We measure the extent to which the exports of agriculture, mining and livestock are associated with deforestation, and we establish a causal link by relying on a measure of foreign demand as a source of exogenous variation for the export variable.

We find evidence that agricultural exports are associated with deforestation. Municipalities with 10% more agricultural exports are associated with 0.3% less forest cover area. The estimations imply that the average growth of agricultural exports during the period analyzed is associated with an annual reduction of 41 thousand hectares of forest cover, equivalent to 25% of the average annual deforestation in the country. Such change in forest cover is associated with roughly 4.9 million tons of carbon emissions per year. The evidence behind livestock is weaker, with results not always statistically significant. We found no relationship between mining exports and deforestation during the period of analysis.

An important finding is that the impact of agricultural exports on deforestation is ameliorated when the production associated with these exports is located in some of the areas that the country has designated as protected, where production techniques must be sustainable. This result is consistent with the notion that a growth in exports that depends more on the intensity of production and technology improvements and less on the expansion of the agricultural frontier will have a lower impact on deforestation.

The last result indicates that there is no linear relationship between agricultural exports and deforestation, which in turn suggests some areas of public policy. For instance, governments could implement regulations in specific areas to encourage sustainable land use and prohibit deforestation. Governments can also consider offering incentives for forest conservation. For instance, there could be financial incentives to landowners to preserve forests or restore previously deforested areas, making it economically viable to maintain forests alongside agricultural activities. Governments could also consider supporting technological advances in agriculture, such as precision farming and improved crop varieties, which could enable higher yields without the need for significant land expansion.

These are examples of policies that seek to address the problem of carbon emissions at its source and thus, are more likely to be dominant from both environmental and welfare perspectives than simply restricting trade flows. In a world increasingly concerned about climate change, there is mounting pressure to consider trade-related measures to address it. But the effectiveness of reducing carbon emissions by limiting trade is an open question. Before considering trade distorting measures, it is worth examining an array of other measures that offers incentives to encourage sustainable land use at its source.

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