Foreign Demand, Soy Exports, and Deforestation*

Léa Crepin[1,2] Clément Nedoncelle[1]

[1] *Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France*

[2] *Climate Economics Chair, Palais Brongniart, 28 Place de la Bourse, 75002 Paris, France.*

Abstract

We evaluate the credibility of demand-side policies to curb deforestation rates. Demand-side policies are considered important drivers of deforestation and soy demand. The academic literature remains mostly silent regarding its potential impacts. We focus on the universe of soy, originating from Brazil, using disaggregated export and production data at the municipality - exporter - destination and year level (TRASE). We estimate whether changes in foreign demand are related to soy exports and soy-related deforestation. Then, we evaluate the role played by soy exporters' networks and market structure in shaping this elasticity.

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1 Introduction

Increased foreign demand for agricultural commodities has been driving deforestation in tropical regions (Defries et al., 2010; Pendrill et al., 2019). Tackling deforestation and curbing forest conversion rates is among the top priorities of policymakers in light of climate change issues. Existing policies include soy moratorium, priority list, protected areas, monitoring, fines for bad producers, changes in access to credit, among others. The common characteristic of these policies is that they are supply-side policies. Indeed, they target producers and intend to change producer behavior directly.

Whereas these policies are effective (Heilmayr et al., 2020; Assunção et al., 2020), complementary policies are necessary and are envisaged by policymakers. There are international and national initiatives to implement demand-side policies to curb deforestation in the producer countries. For instance, the European Green Deal includes measures to favor sustainable supply chains. In France, a strategy to fight against "imported deforestation" has been set up, and actions include the relocation of plant protein production in the national territory. The main argument in favor of these demand-side policies is that changes in consumer behavior will help curb deforestation rates.

The objective of the current paper is to assess the credibility of these demand-side policies. Are changes in consumer demand related to deforestation? To answer this question, we settle on a specific framework and tackle this question from the soy perspective. Indeed, conversion from forests to soy-producing areas (potentially indirectly through conversion into pastures first) is a major driver of deforestation (Song et al., 2021). We leverage this mechanism and estimate whether changes in world demand for soy are related to deforestation. Whereas soy supply is responsible for deforestation, the role of demand for soy remains an open question. The credibility of demand-side policies relies on this question.

To answer this question, we use data covering the universe of soy production from Amazonia and Cerrado in Brazil. Indeed, these two biomes are iconic places of deforestation, and the soy production in these places is related to substantial direct and indirect deforestation (Jia et al., 2020). Moreover, most of the soy produced in Brazil is for exports (78%). As a result, changes in soy production could plausibly be driven by changes in foreign demand. Second, the soy export market is also very specific compared to other commodities. Whereas soy is a homogeneous commodity, soy exporters' market is hourglass-shaped, with few but very large exporters with a competitive fringe of sellers. Our analysis will account for these specific features explicitly.

Our analysis combines location and firm-specific soy production and export data with aggregate trade data informing soy demand (imports) by destinations. In this context, we estimate a firm-level gravity equation relating firm-municipality-destination export flows (in values) to standard firm-level trade determinants and destination-specific soy demand. Combined with demanding fixed effects, identification relies on the exogeneity of soy demand from abroad that soy exporters face.

Our analysis delivers two main results. On the one hand, we estimate an average micro-level elasticity of soy exports to foreign demand of around 0.2 across specifications. On average, exporting firms increase their exports by 0.2% for a 1% change in foreign demand. This result is robust to including a wide array of potentially omitted variables, to potential endogeneity issues, to alternative estimations issues. This high elasticity confirms the credibility of demand-side policies, even though the magnitude of the coefficient remains small.

On the other hand, we document that the average response above hides significant heterogeneities across exporters and across locations in Brazil. If changes in demand affect soy exports, the response will vary across places and across exporting firms. In particular, our analysis highlights that larger cities, with fewer and smaller exporters, experience a larger elasticity. We also estimate heterogeneous effects of the same demand shocks across places depending on past deforestation levels: estimated effects are larger in places with lower past deforestation patterns.

As a result, demand-side policies could effectively curb soy production but would imply reallocations of soy production across places and firms. These reallocations are important as they would redistribute exports and production across firms, in favor of the smallest exporters, and into deforestation-prone places.

To check whether our estimates suggest that a large negative shock on foreign demands would translate into a substantive slowdown of deforestation rates, we finally estimate the elasticity between agricultural production and deforestation and present the effect of a reduction of 20% of foreign demand on deforestation. Although this would only translate to a decrease of 2% in deforestation for the smaller firms, the reduction of deforestation attributed to the larger firms would be around 15%. This is a substantial reduction, especially since larger firms deforest more.

This paper builds upon and contributes to three strands of the literature. Firstly, it adds to the growing body of research on the link between trade and deforestation. While previous studies have identified several channels through which trade openness may affect deforestation, including agricultural market prices, land-use value, imported agricultural input costs, and productivity (Abman and Lundberg, 2019), empirical evidence of the effect of trade on deforestation has been limited (Balboni et al., 2022). However, recent studies have provided new insights into this relationship. (Abman and Lundberg, 2019) shows that deforestation increases following RTAs, and that this effect is mediated by agricultural trade. Tracking the deforestation in trade flows, (Pendrill et al., 2019) shows that a large part of tropical deforestation can be attributed to foreign consumer countries, especially for soybean. Also, the recent microdata of the supply chains documents the involvement of transnational firms in this process (West et al., 2018). This paper builds on this literature by quantifying the heterogeneous effects of changes in foreign demand on supply and deforestation, considering geographic and firm-level characteristics.

In that sense, we also build on the international economics literature that considers the importance of firm heterogeneity in shaping the patterns of international trade (Melitz, 2008). Here, we empirically show how the heterogeneity in firms in the soybean markets affects the elasticity of supply to foreign demand, and how this heterogeneity matters for the effect of demand-side policies on deforestation.

Finally, this paper adds to the growing body of literature on policies to slow the rate of deforestation. Recent research has considered trade policies as instruments to encourage conservation in countries that may otherwise deforest their territories (Balboni et al., 2022). While some studies have proposed import tariffs as a means of reducing deforestation (Harstad, 2022; Domínguez-Iino, 2022) and others have examined the efficiency of bans (Busch et al., 2022; Villoria et al., 2022), the effectiveness of these policies remains controversial. This paper contributes to this literature by examining how changes in foreign demand can be transmitted heterogeneously to deforestation through firms and how changes in foreign demand could translate into a decrease in deforestation. Our results on demand-side policies suggest that, although acting on foreign demands would not transmit homogeneously across the market, the adaptation of the supply to the changes in demand could indeed slow down the deforestation process in producing countries.

The rest of the article is organized as follows. The next section details the data sources and presents the main variables used in the empirical analysis. Section 3 provides an overview of the empirical methodologies employed. Section 4 describes the main results of the analysis. Section 5 presents a quantification exercise. The final section concludes and discusses the results.

2 Data and descriptive statistics

2.1 Data sources

We use data covering the universe of soy exports, soy production, and foreign demand, from 2004 to 2017, in Amazonia and Cerrado, in Brazil. This section provides summary information on our data construction and measurement.

Soy firm-level exports To identify soy export flows, we rely on the TRASE database (Godar, 2018). This database is constructed from customs records and maps trade flows (in physical quantities and port of export FOB values) from source cities to destination markets and the agribusiness firms intermediating the transactions. The unit of observation in our analysis is at the exporter group $\times$ municipality $\times$ destination country $\times$ year level. Transactions include those in raw or processed form (soybean cake, meal, oil). A limitation of this database is that it is partially modeled, and 14% of the trade value is not successfully attributed to transactions. Moreover, the TRASE database does not match exactly our demands calculated with BACI because the destination reported is the first country of export.

Firms characteristics The TRASE database allows us to identify exporters' characteristics. Namely, we can measure total firm exports, the number of destinations each firm serves, as well as the sourcing strategies of firms across municipalities.

Market structure The TRASE dataset also allows us to characterize the market structure of soy exports in Brazil. Indeed, TRASE provides consistent information about traders, source cities, and destination markets. We can measure many aggregates informing on the market structure and which may be driving forces behind the main elasticity. We compute by city, the number of exporters (sourcing from this specific city, eventually serving a specific destination), the average exports of these firms, the rank of each firm in the hierarchy and other aggregates.

Soy demands measures We measure the soy demands arising in importing countries addressed to Brazil using the BACI Database. BACI is an international trade database stemming from the harmonization of the COMTRADE database, in which the trade flows reported by exporting and important countries sometimes differ (Gaulier and Zignago, 2010). We select the bilateral trade flows of the six-digit Harmonized System products associated with soybeans (HS6 120100, Soya beans; whether or not broken) and aggregate by destination d and year t the total soy demand: $SoyDemand_{dt} = \sum_{o} X_{odt}^{soy}$. In benchmark estimations, we exclude human consumption uses of soybean (in HS 120810, 150710, 150790, 230400 – vegetable oils, flours, and meals), representing around 15% of total use of soy worldwide, then used for robustness.

City characteristics We also collected some city-specific time-varying variables, which can be determinants of firm-specific and aggregate trade. Among others, we use data on municipality GDP, population, distance to the main port.

Deforestation Our paper investigates the role played by past deforestation on the exports-demand elasticity. To measure deforestation, we use the PRODES data, aggregated at the municipality level. Because most of the soy expansion takes place in the Cerrado, an ecosystem of tropical savanna not included in the forest definition, we extend the analysis beyond deforestation and consider more broadly the effects of the changes in demand on the changes in natural vegetation. This ecosystem, with low legal protection compared to the Brazilian Amazon, is currently experiencing high conversion rates (five times as high as deforestation rates in the Amazon before the Soy Moratorium) in which soy plays a direct and significant role (Rausch et al., 2019). We rely on the MapBiomas database (Souza and Azevedo, 2017).

Table 1: Distribution of world imports of soy (2004 - 2017)

Country	% of world imports
China	.5518215
Netherlands	.0408129
Mexico	.0375814
Japan	.0357707
Germany	.0354034
Spain	.0326716
Taiwan, Province of (China)	.0235492
Thailand	.0195805
Indonesia	.0184115
Iran (Islamic Republic of)	.0155059
Egypt	.0152757
Turkey	.015264
Italy	.0149479

2.2 Market description

Using our datasets, we document 3 main facts of importance for the analysis.

Fact #1. Exporters face an increase in demand.

Figure 1 illustrates how the world demand for soybean increased dramatically over the last ten years, largely driven by the Chinese demand. The demand from China is expected to increase, as is the global consumption of this commodity in the years to come. The Brazilian supply mainly satisfied the demand, especially in the last decade. 828 Brazilian municipalities supplied China with soybean in 2004 through 124 exporter groups. They were 1436 through 117 exporter groups in 2017.

Table 1 reports the share of world soy imports from each country. China is by far the largest importer, accounting for over 55% of imports. Exporters and municipalities typically serve multiple destinations. Over our period (2004 to 2017), municipalities served on average 18 countries and exporter groups 6 countries, although this number varies widely across exporters, as Figure 1 shows. Exporters and municipalities should therefore face multiple demand shocks from importing countries.

Fact #2. The soybean market is hourglass-shaped, with multiple producers, destination countries, and a few but large trading firms.

Our sample contains 786 distinct exporters. However, a few firms dominate the market. Figure 2 shows the market share of the top 4 firms (ADM, Bunge, Cargill and Louis Dreyfus), also called the ABCD traders. These 4 firms alone control more than half of the soybean market in Brazil. On average, they have a vast sourcing pattern and present a high market share in their sourcing municipalities compared to smaller firms (Table 2). We identify these 4 firms and will use this small group as evidence of

Figure 1: Demand from BACI trade flows

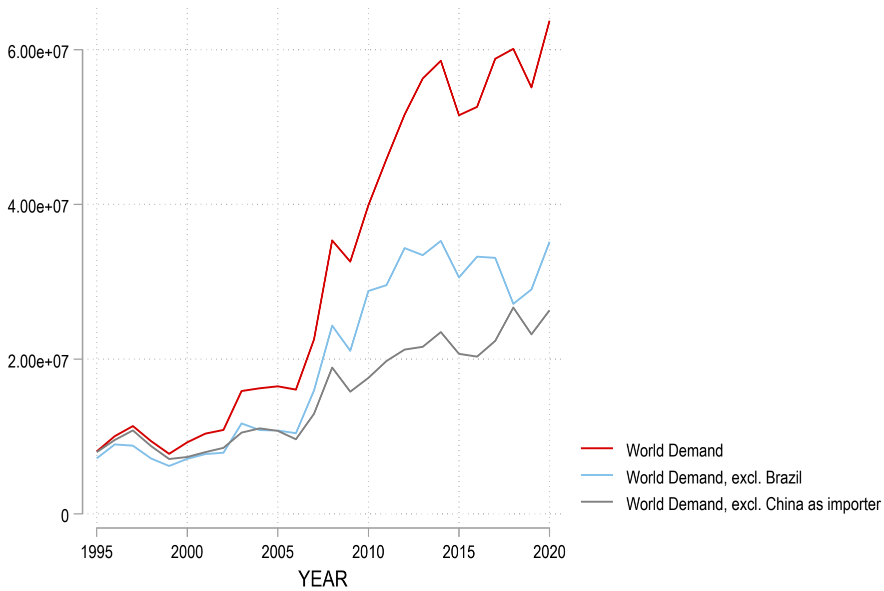


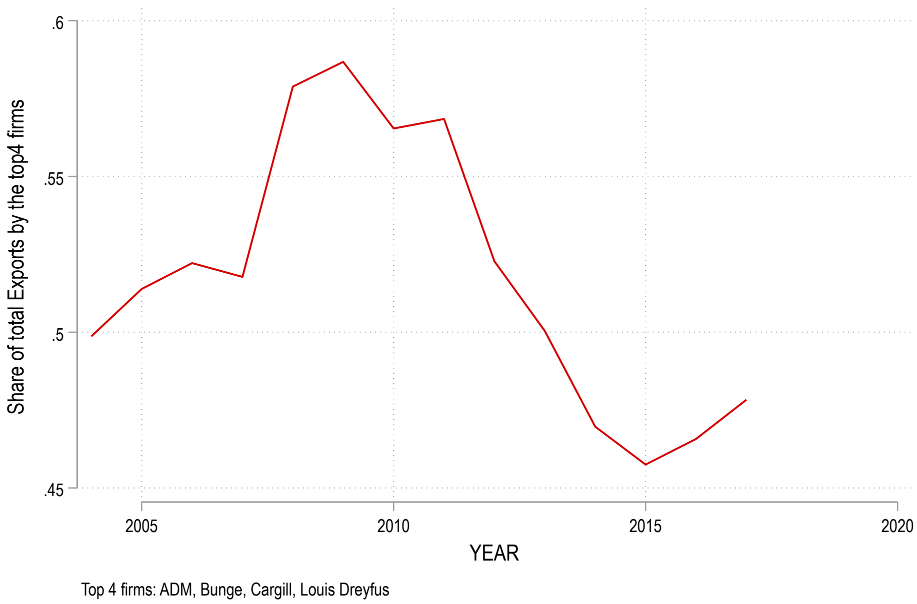
Table 2: Soybean market structure. Descriptive statistics.

	Traders ABCD	Other firms
Average market share (%)	13.4 (6.00)	0.059 (0.371)
Average market share in the sourcing municipalities (%)	37.6 (3.91)	7.56 (14.1)
Average number of sourcing municipalities	931 (277)	9.51 (34.14)
Average number of destinations	63.2 (4.50)	5.32 (7.93)

Fact #3. The largest firms tend to compete with smaller firms within the municipalities.

Figure 3 illustrates the sourcing municipalities of the exporters in 2015. Each row is an exporter and a dot represent a positive sourcing (i.e. the firm exports soy produced in city c). The top-4 traders are represented in green. Green dots represent the presence of a top-4 firm. There is only a small overlap of the sourcing patterns of these traders, but municipalities trade with multiple firms. We can therefore expect competition effects between exporters within municipalities, both between small and large exporters and across large exporters.

Figure 2: Market shares of the ABCD traders



3 Empirical strategy

3.1 Micro-level elasticity

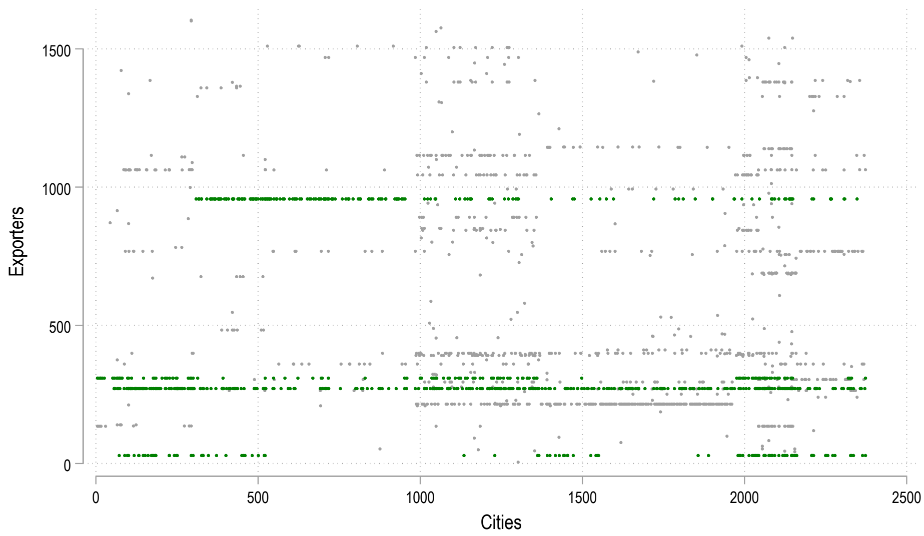
Our main estimation strategy of the micro-level elasticity is based on regressions of exports of soybean per firm, municipality, and destination country on the soybean demand from a destination country. We choose this level of analysis to estimate the reaction of a firm sourcing from a city to a demand shock from a destination country. In formal terms, the linear regressions follow equation:

$$\text{Exports}_{fcdt} = \alpha \text{Soy Demand}_{dt} + \beta \text{Controls}_{dt} + \mathbf{FE} + \varepsilon_{fcdt} \tag{1}$$

where Exports_{fcdt} is the value of the soy exports of firm f from city c to destination country d in year t, Soy Demand_{dt} is the total soy imports by destination d from anywhere in the world, including Brazil, from BACI. Controls_{dt} is a vector of time-varying destination-specific trade determinants such as destination observables (foreign GDP, foreign GDP per capita, population, foreign agricultural output, ...).

Our specification also includes a set of fixed effects (FE). The main results are obtained using firm-city-destination fixed effects and firm-city-time fixed effects. The former set of fixed effects absorbs variance across individuals. Coefficients are thus identified from variation across time for a given individual (i.e. an exporter-source city-destination country group). These fixed effects absorb the effect of many time-invariant determinants of trade, such as: distance with destination country (as all exporters are located in Brazil), pre-existence of a relationship between a firm and a destination country. It also absorbs trade determinants that do not vary in our sample period, such as the existence of a regional trade

Figure 3: Sourcing patterns of the trading firms (data 2015)



agreement between Brazil and a destination (as Brazil did not sign any new agreement between 2004 and 2017 with soy exports destinations). We also include a firm-city-year set of fixed effects that control for time-varying heterogeneity across cities (such as GDP per capita, the share of agriculture in local GDP, ...) as well as across firms (such as total firm exports, number of destinations, number of sources, etc.). Note that fixed effects also exclude the potential non-random selection of sourcing cities at the firm-level: estimations are performed within a given firm network of sourcing and destination at the firm level. All the adjustment must therefore take place within a given network.

Our coefficient of interest is α, which we expect to be positive as exports and demand should go in the same direction. This coefficient captures the average elasticity of exports to demand. Beyond significance, the value of α will inform the credibility of demand-side policies. Indeed, these policies would have any effect only if α is large enough, and to a larger extent as long as the cost of the policy is not too high.

Regarding inference, ε_{fdct} is a random error term. We allow errors to be correlated within groups of destination-year, and cluster the standard errors at this level (which is also the level of the demand shocks).

We estimate equation (1) using a PPML estimator, as standard practice regarding trade flows (Santos Silva and Tenreyro, 2006). We will check the sensitivity of results when using alternative estimators (OLS), subsamples and specifications.

3.2 Heterogeneity

After estimating the average export elasticity of firms sourcing from a city to a demand shock from a destination country, we investigate the heterogeneous response across cities and firms. We estimate:

$$\begin{aligned}\text{Exports}_{fcdt} &= \alpha\text{Soy Demand}_{dt} + \beta\text{Controls}_{dt} + \delta_1(\text{Soy Demand}_{dt} \times \text{Controls}_{f(t-1)}) \\ &+ \delta_2(\text{Soy Demand}_{dt} \times \text{Controls}_{c(t-1)}) + \delta_3(\text{Soy Demand}_{dt} \times \text{Controls}_{c(d)t}) \\ &+ \mathbf{FE} + \varepsilon_{fcdt}\end{aligned} \tag{2}$$

where the set of δ captures the differential effects of the same soy demand shock across firms, cities, and market structure observables, respectively.

First, to identify which exporters capture the changes demand, we condition the impact of the demand shocks on observables at the firm level ($\text{Controls}_{f(t-1)}$). Variables include the lagged number of destinations and the number of sourcing municipalities per firm. Overall, these variables intend to capture exporter size.

Second, to determine *where* the additional demand is satisfied from, we focus on the interaction between demand shock and municipalities' characteristics (Controls_{ct}). These characteristics include the GDP of the sourcing municipalities, their GDP per capita, the number of firms operating in the city, how many of the "ABCD traders" (ADM, Bunge, Cargill, and Louis Dreyfus, the leaders in soy trade management) operate in the municipality, the mean exports of a municipality, as well as its past deforestation levels.

Finally, to explore whether the response is shaped by competition in the city and destination markets, we use controls at the city and/or destination and year level ($\text{Controls}_{c(d)t}$).

In formal terms, we will use a wide array of fixed effects to use the correct identifying variation and control for many unobserved shocks. For instance, when investigating the variation across cities, we will use (at least) a city-destination-year fixed effect to account for observables and unobservables at this level and use the remaining variation across firms only. The whole set of fixed effects will also account for most of the unconditionnal effects of these variables: the unconditional effect of firm size is for instance capture in the firm(-city)-year fixed effect. Importantly, we will use a destination-year fixed effect: this will absorb the unconditional effect of the demand shock (acting as if all firms faced the same demand shock) but the interaction between demand and observables will remain identifiable.

4 Results

4.1 Average Elasticity

Results in Table 3 support a positive and significant correlation between soy demand in destinations and firm-level exports. Column 1 includes only import demand as trade driver and the benchmark set of fixed effects (firm-city-destination and year-fixed effects). Column 2 considers a more demanding fixed effects structure, including a firm x city x year fixed effect absorbing the major trade determinants at both the firm and the aggregate levels. The positive elasticity is independent of the set of fixed effects included in the estimation and of the subsequent change in samples (excluding singletons in the fixed effect dimensions). Columns 3 and 4 consider destination-specific time-varying trade determinants and find a positive impact of agricultural land in destinations and of destination GDP per capita on soy imports. These variables are proxys for animal feed demand. We do not estimate significant impact of import tariffs on primary products nor of the average yield of cereals in destinations. Controlling for these determinants dampens the estimated elasticity to half its benchmark value, around 0.2.

Table 3: PPML estimations

	Dep. Variable: Firm-level Exports, (X_{fcdt})			
	(1)	(2)	(3)	(4)
Soy Demand dt	0.445***	0.455***	0.203***	0.180***
	(0.066)	(0.061)	(0.033)	(0.032)
Dest GDP pc.			2.344***	2.294***
			(0.141)	(0.159)
Agric. Land in Destination				1.327**
				(0.531)
Av. Cereal Yield (kg/ha)				0.218
				(0.171)
Average Tariffs (primary products)				-0.102
				(0.196)
Observations	210672	117206	110855	96798
R^2				
Fixed Effects	fcd t	fcd fct	fcd fct	fcd fct
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Using this 0.2 elasticity, quantification is as follows: a 1% increase in foreign soy demand increases soy exports (in value) by 0.2% on average. One standard deviation of soy demand (2.32) is related to a 0.5%increase in exports in our sample. This value is the average effect of changes in demand across firms and municipalities.

4.2 Effects Across Trade Margins.

Table 4 decomposes the average elasticity of soy exports to demand into an intensive and an extensive margin of trade, respectively. Indeed, the baseline sample includes both zero trade flows and positive flows.

As for the intensive margin, we estimate equation 1 on the sample of positive trade flows, and results are presented in columns 1 and 2. As for the extensive margin (entry and exit), we regress a dummy equal to 1 if the trade flow is positive. Both estimations are run using a PPML estimator (see robustness section for this issue). We estimate that soy demand affect soy exports through both trade margins. In quantitative terms, both trade margins are of similar size, even though point estimates are larger for the extensive margin of trade. It implies that soy demand changes are likely to affect not only the amount of exports, conditional on presence, but also the presence of an exporter.

Table 4: Intensive and Extensive Margins

	Dep. Variable: Firm-level Exports (X_{fcdt})		($X_{fcdt} > 0$)	
	(1)	(2)	(3)	(4)
Soy Demand dt	0.095***	0.080**	0.144***	0.135***
	(0.031)	(0.032)	(0.019)	(0.021)
Dest GDP pc.	1.971***	1.903***	0.590***	0.561***
	(0.140)	(0.147)	(0.109)	(0.135)
Agric. Land in Destination		0.999**		0.892***
		(0.483)		(0.298)
Av. Cereal Yield (kg/ha)		0.515***		-0.159
		(0.136)		(0.101)
Average Tariffs (primary products)		-0.303***		-0.091
		(0.111)		(0.108)
Observations	56840	47960	110855	96798
R^2				
Fixed Effects	fcd fct	fcd fct	fcd fct	fcd fct
Cluster Level	dt	dt	dt	dt
Sample	Exports>0	Exports>0	full	full

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

4.3 Heterogeneous effects

Turning to heterogeneity, in this subsection, we document the differential effect of the demand shocks across firms, across cities, and depending on market structures and on previous deforestation patterns. These patterns are particularly important as they inform on the heterogeneous and differential effects of the potential demand-side policies.

Heterogeneity: Across Firms. Using variation across firms, holding city-destination-year observables constant (thanks to the fixed effects), Table 5 finds robust differential effects of increased demand across exporters. Results support that larger exporters – measured in terms of the (lagged) number of foreign destinations, (lagged) number of sourcing municipalities, (lagged) total exports, and "being a top-4 firm" dummy – capture most of the additional demand. Any increase in soy demand is mainly captured by the largest exporters.

Table 5: Heterogeneity: Firms

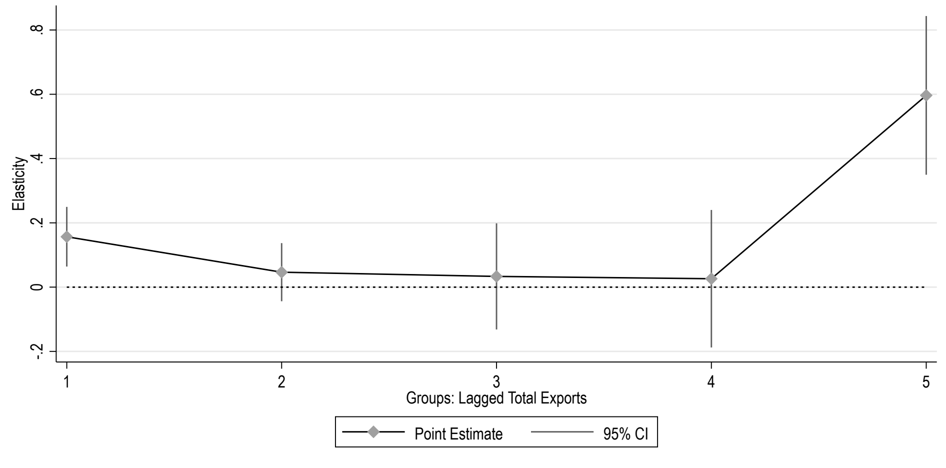
	Dep. Variable: Firm-level Exports (X_{fcdt})			
	(1)	(2)	(3)	(4)
Soy Demand dt × L.Nb Dest.	0.085***			
	(0.023)			
Soy Demand dt × L.Nb Sources		0.046***		
		(0.009)		
Soy Demand dt × L.Firm Exports			0.048***	
			(0.009)	
Soy Demand dt × (Dtop4=1)				0.097***
				(0.024)
Observations	18583	18583	18583	20564
R^2				
Fixed Effects	cdt fct	cdt fct	cdt fct	cdt fct
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

How large is the differential effect? Figure 4 provides a visual interpretation of the heterogeneous effects across firms. Grouping firms into 5 bins –depending on their lagged total exports–, we re-estimate the general model on each group separately. The smallest firms are almost unaffected by the increased demand, as coefficient is close to 0 or insignificant. Only the top 20% of firms yield a positive and significant elasticity, close to 0.6. The positive average coefficient is determined by the top firms, only. The largest firms drive the elasticity upwards.

Heterogeneity: Across Cities. We then estimate the conditional impact of city observables on the elasticity. Table 6 shows results and specification controls for firm-destination-year fixed effects and the identifying variation is across cities. Results support robust differential effects of an increase in demand across soy-producing municipalities. In other words, a change in foreign demand does not have the same impact across soy-producing municipalities. We estimate that, conditional on the soy demand change, the impact is larger is cities with smaller GDP per capita (col. 1), cities that are closer to ports (col. 2), and that have crushing and crucially refining capacities (cols. 3 and 4). Municipalities with those characteristics tend to capture most of the additional demand and could thus be more harmed by

Figure 4: Differential effects of demand variation across groups of firm size.



a decrease in demand abroad.

Table 6: Heterogeneity: Geography

	Dep. Variable: Firm-level Exports (X_{fcdt})			
	(1)	(2)	(3)	(4)
Soy Demand dt × GDP per Cap. (city)	-0.029***	-0.018*	-0.015	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)
Soy Demand dt × Distance to Port		-0.033**	-0.031**	-0.033**
		(0.013)	(0.013)	(0.013)
Dcrushing=1			0.663**	1.522***
			(0.288)	(0.414)
Soy Demand dt × Dcrushing=1			0.028*	-0.016
			(0.016)	(0.027)
Drefining=1				-1.919***
				(0.468)
Soy Demand dt × Drefining=1				0.095***
				(0.034)
Observations	172017	172017	172017	172017
R^2				
Fixed Effects	fdt ct	fdt ct	fdt ct	fdt ct
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

In terms of importance, note that the differential elasticities are of much smaller magnitude than those estimated across firms.

Heterogeneity: Previous deforestation patterns. Finally, where are the additional demands satisfied from? Table 7 investigates the potential differential effect across municipalities, specifically according to the past deforestation levels. Indeed, the same soy demand could lead to soy production in places with either no deforestation issues or in deforestation-prone places. The resulting deforestation patterns could thus be affected by foreign demand policies.

We rely on deforestation data from Mapbiomas and condition the impact of soy demand on firm-level exports along the previous patterns of deforestation (to avoid endogeneity issues too). Table 7 presents results, focusing on the mitigating impact of past deforestation. We find that the additional soy production is satisfied from places with *lower* past deforestation. The increased soy production to satisfy demand is estimated to be more located in places with lower previous deforestation patterns, measured in t-1 (col. 1) and up to t-3 (cols. 2 to 4).

Table 7: Heterogeneity: Deforestation Levels

	(1)	(2)	(3)	(4)	(5)
Soy Demand dt × GDP per cap.	-0.018*	-0.018*	-0.020*	-0.014	-0.030*
	(0.010)	(0.011)	(0.011)	(0.012)	(0.016)
Soy Demand dt × L.Deforesta. (Mapbiomas)	-0.007***			-0.005***	
	(0.001)			(0.001)	
Soy Demand dt × L2.Deforesta. (Mapbiomas)		-0.007***		-0.003***	
		(0.001)		(0.001)	
Soy Demand dt × L3.Deforesta. (Mapbiomas)			-0.007***	-0.004***	
			(0.001)	(0.001)	
Soy Demand dt × L.Deforesta. (t*t-5) (Mapbiomas)					-0.009***
					(0.001)
Observations	134501	121405	108935	87570	47309
R^2					
Fixed Effects	fdt ct	fdt ct	fdt ct	fdt ct	fdt ct
Cluster Level	dt	dt	dt	dt	dt

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Heterogeneity: Market structure The soy export market in Brazil is not a textbook-like competitive market, with atomistic, price-taking producers. On the contrary, the market is made of a few large, oligopolistic firms, and of a competitive fringe. We investigate whether this particular market structure shapes the elasticity of exports to demand.

Table 8 confirms this hypothesis. Competition shapes the geography of soy production. Conditional on soy demand, and controlling for GDP per capita, production will be larger in cities with fewer firms (col. 1), fewer firms serving the same destination (col. 2) and fewer top-4 firms (col. 3).

5 Robustness checks

The previous section documented the positive but small average elasticity of exports to soy demand. Then, it also showed that the average elasticity hides significant and important heterogeneity across

Table 8: Heterogeneity: Cities

	Dep. Variable: Firm-level Exports (X_{fcdt})			
	(1)	(2)	(3)	(4)
Soy Demand dt × L.GDP per cap.	-0.016	-0.061***	-0.027*	-0.035***
	(0.012)	(0.013)	(0.016)	(0.012)
Soy Demand dt × L. Nb Firms in c-t	-0.018**			
	(0.008)			
L.Nb Firms in c-d-t		1.831***		
		(0.229)		
Soy Demand dt × L.Nb Firms in c-d-t		-0.083***		
		(0.014)		
L. Nb Top 4 firms			2.173***	
			(0.304)	
Soy Demand dt × L. Nb Top 4 firms			-0.109***	
			(0.020)	
L.Mean Exports (c-d-t)				0.382***
				(0.080)
Soy Demand dt × L.Mean Exports (c-d-t)				-0.001
				(0.006)
Observations	134501	70199	46635	70199
R^2				
Fixed Effects	fdt ct	fdt ct	fdt ct	fdt ct
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

firms and in space. This section confirms the robustness of these results, along various dimensions. Results are displayed in Appendix A.

5.1 Exports measures

Excluding China First, as China is the top importer and account for more than half of the world imports, we cannot exclude that the specific China behavior may affect the elasticity. Table A.1 replicates the main estimations, excluding China from the sample. This change of sample does not affect our conclusions.

Exports in quantities, and unit values Second, we replicated the estimations using firm-level exported quantities. Results are presented in Table A.2. Third, we replicated our main estimation on unit values (defined as ratio of exports value over exported quantities). Results are presented in Table A.3.

5.2 Soy Demands measures

Soy Demand in Quantities Conclusions are unaffected by our choice of the soy demand measures. Indeed, Table A.4 presents results when using world soy demand in quantities (from BACI) instead of the benchmark export values.

Soy Demand in for other uses. In benchmark estimations, we excluded human consumption uses of soybean. Table A.5 includes other uses of soy in the analysis. In particular, we account for the demand of soy in HS codes/chapters 120810, 150710, 150790, 230400, i.e. vegetable oils, flours, and meals. These other uses represent around 15% of total use of soy worldwide.

Excluding demand from Brazil We cannot exclude that Brazil is A.6

5.3 Estimation issues

OLS estimation Table A.7 shows results when estimating equation 1 with the log of exports as dependent variable and using an OLS estimator. Focusing on the universe of positive trade flows only, Table A.7 supports that the main elasticity value is affected by the choice of the estimator and lies on average around 0.1. This is about half the value of the benchmark estimates. One way to interpret this result is: the OLS estimates captures the effect of demand on exports at the intensive margin only, whereas the PPML estimates identify the effects at both the intensive and the extensive margins of trade. Hence, it is not surprising to obtain smaller point estimates.

Clustering of standard errors Inference is robust to the use of alternative standard error clustering levels: whereas benchmark results were based on destination-year clustering, inference is confirmed when country-year clustered errors (Table A.8) or with two-way country-year and destination-year clusters (Table A.9).

5.4 Placebo: other-than-soy exports

We do not capture a general trend toward Brazilian goods or other trends in import behavior. We regressed the firm-level soy exports on a demand that is unrelated to soy. We thus computed the total imports of goods from Brazil and excluded soy. In table A.10, plugging this non-soy demand in the estimations provides mainly non-significant coefficients, as expected.

6 Quantification: effect on deforestation

So far, we have discussed how variations of demand are captured heterogeneously by some firms and municipalities. Relying on this previous result, we now aim to quantify the effect of a shock on foreign demands on deforestation.

The effects of changes in demand on deforestation can be decomposed into two elasticities. First, demand is captured heterogeneously by firms and municipalities, which is represented by our previously estimated micro elasticities of soy exports to foreign demands. Then, how this translates into deforestation is measured by the deforestation to supply elasticity. We quantify the effects of variations of demand on deforestation using the following formula:

$$\text{Def}_f = \text{ elasticity supply-def}_f \times \text{ elasticity supply-demand} \times \text{demand}_f \tag{3}$$

The first step is to estimate the missing elasticity of deforestation to supply. To do so, we regress deforestation rates on soybean production at the year and municipality level following (x). α is the elasticity of interest, FE are municipality and year fixed effects, X_{ct} is a set of controls, which includes agricultural GDP, GDP per capita, and population growth.

$$\text{Def}_{ct} = \alpha \text{ Soy production}_{c,\text{t-4 to t-1}} + \sum_i \beta_{it} X_{it} + \mathbf{FE} + \epsilon_{ct} \tag{4}$$

We test the sensibility of our results to several data sources and specifications. Our preferred estimate is ..., with a confidence interval ranging from ... to ... . It is based on data from MapBiomas for the conversion of natural vegetation, on the soybean production reported in tonnes by the IBGE (the Brazilian Institute of Geography and Statistics). The variables *Soy production* and *Def* were transformed with IHS rather than logarithms due to the presence of many zeros in the dataset. *Def* is calculated as the average of the increments of deforestation between $t-4$ and $t-1$ because there is usually a time lag of a few years between the deforestation event and the soy production (ref).

IN PROGRESS

7 Conclusion and Discussion

The current paper aims to assess the credibility of these demand-side policies. Are changes in consumer demand related to deforestation? To answer this question, we settle on a specific framework and tackle this question from the soy perspective. Indeed, conversion from forests to soy-producing areas (potentially indirectly through conversion into pastures first) is a major driver of deforestation (Song et al., 2021). We leverage this mechanism and estimate whether changes in world demand for soy are related to deforestation. Whereas soy supply is responsible for deforestation, the role of demand for soy remains an open question. The credibility of demand-side policies relies on this question.

Our analysis delivers two main results. On the one hand, we estimate an average micro-level elasticity of soy exports to foreign demand of around 0.2 across specifications. On average, exporting firms increase their exports by 0.2% for a 1% change in foreign demand. This result is robust to the inclusion of a wide array of potentially omitted variables, to potential endogeneity issues, to alternative estimations issues. This elasticity is somehow "good news" for the credibility of demand-side policies.

On the other hand, we document that the average response above hides significant heterogeneities across locations and exporters. If changes in demand affect soy exports, the response will vary across places and exporting firms. In particular, our analysis highlights that larger cities, with fewer and smaller exporters, experience a larger elasticity.

Appendix for

Foreign Demand, Soy Exports, and Deforestation

Léa Crepin[1,2] Clément Nedoncelle[1]

[1] *Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France*

[2] *Climate Economics Chair, Palais Brongniart, 28 Place de la Bourse, 75002 Paris, France.*

A Robustness: Tables

Table A.1: No China

	Dep. Variable: Firm-level Soy Exports			
	(1)	(2)	(3)	(4)
Soy Demand dt	0.182***	-0.518**		
	(0.035)	(0.226)		
Soy Demand dt × L. Firm Exports		0.034***		
		(0.011)		
Soy Demand dt × L.GDP per cap.			-0.023	0.004
			(0.014)	(0.015)
Soy Demand dt × ldistance			0.158***	
			(0.021)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				0.003***
				(0.001)
Observations	80312	61684	52123	52123
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.2: Firm-level exports in quantities

	Dep. Variable: Firm-level Exports Values (1)	(2)	(3)	(4)
Soy Demand dt	0.105**	-0.836		
	(0.044)	(0.572)		
Soy Demand dt × L.Firm Exports		0.046		
		(0.028)		
Soy Demand dt × L.GDP per cap.			-0.022	0.002
			(0.015)	(0.015)
Soy Demand dt × Distance to Port			0.037*	
			(0.019)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				-0.006***
				(0.001)
Constant	-34.731***	-29.694**	8.277***	10.321***
	(9.289)	(12.465)	(3.213)	(2.258)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.3: Unit Values

	Dep. Variable: Firm-level Exports: Unit Values (1)	(2)	(3)	(4)
Soy Demand dt	-0.004	0.292***		
	(0.005)	(0.066)		
Soy Demand dt × L. Firm Exports		-0.014***		
		(0.003)		
Soy Demand dt × L.GDP per cap.			-0.000	-0.003
			(0.002)	(0.002)
Soy Demand dt × Distance to Port			-0.013***	
			(0.002)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				-0.000***
				(0.000)
Constant	5.257***	6.799***	7.791***	6.521***
	(1.084)	(1.325)	(0.405)	(0.303)
Observations	31705	13012	17876	17876
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.4: Soy Demand: Quantities

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Soy Demand dt (Q.)	0.112***	-0.895**		
	(0.036)	(0.438)		
Soy Demand dt (Q.) × L. Firm Exports		0.048**		
		(0.022)		
Soy Demand dt (Q.) × L.GDP per cap.			-0.024*	-0.004
			(0.014)	(0.014)
Soy Demand dt (Q.) × Distance to Port			0.034*	
			(0.018)	
Soy Demand dt (Q.) × L.Deforesta. (Mapbiomas)				-0.006***
				(0.001)
Constant	-25.700***	-23.273*	14.993***	17.199***
	(9.479)	(12.499)	(3.119)	(2.225)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.5: Other Uses of Soy

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Soy Demand (other uses)	0.880***	1.107***		
	(0.113)	(0.365)		
Soy Demand (other uses) × L. Firm Exports		-0.014		
		(0.019)		
Soy Demand (other uses) × L.GDP per cap.			0.013	0.024
			(0.018)	(0.017)
Soy Demand (other uses) × Distance to Port			-0.017	
			(0.023)	
Soy Demand (other uses) × L.Deforesta. (Mapbiomas)				-0.010***
				(0.001)
Constant	-19.909***	-21.648**	16.602***	12.752***
	(7.169)	(9.178)	(3.691)	(2.660)
Observations	96798	74003	63101	63101
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.6: Soy demand, excluding Brazil

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Soy Demand (excl. Brazil)	0.366***	1.329		
	(0.093)	(0.969)		
Soy Demand (excl. Brazil) × L. Firm Exports		-0.041		
		(0.045)		
Soy Demand (excl. Brazil) × L.GDP per cap.			-0.017	0.011
			(0.023)	(0.024)
Soy Demand (excl. Brazil) × Distance to Port			0.036	
			(0.036)	
Soy Demand (excl. Brazil) × L.Deforesta. (Mapbiomas)				-0.009***
				(0.002)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.7: OLS

	Dep. Variable: log Firm-level Exports			
	(1)	(2)	(3)	(4)
Soy Demand dt	0.061*	-0.541**		
	(0.034)	(0.231)		
Soy Demand dt × L. Firm Exports		0.028**		
		(0.012)		
Soy Demand dt × L.GDP per cap.			0.015	0.019*
			(0.010)	(0.010)
Soy Demand dt × Distance to Port			0.014	
			(0.014)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				-0.001
				(0.001)
Constant	-17.313**	-16.344	9.507***	10.796***
	(7.104)	(10.782)	(1.846)	(1.324)
Observations	47960	33513	37092	37092
R^2	0.850	0.842	0.832	0.832
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

OLS estimations. Standard errors in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Table A.8: Altertnative clustering: municipality-year

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Soy Demand dt	0.122***	-0.964**		
	(0.029)	(0.490)		
Soy Demand dt × L. Firm Exports		0.052**		
		(0.024)		
Soy Demand dt × L.GDP per cap.			-0.025	-0.004
			(0.022)	(0.020)
Soy Demand dt × Distance to Port			0.033*	
			(0.018)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				-0.006***
				(0.002)
Constant	-25.246***	-23.010**	15.316***	17.267***
	(6.291)	(10.183)	(3.159)	(3.101)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	ct	ct	ct	ct

Standard errors in parentheses, clustered by c-t.

* p<0.1, ** p<0.05, *** p<0.01

Table A.9: Two-way clustering: municipality-year + destination-year

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Soy Demand dt	0.122***	-0.964*		
	(0.040)	(0.557)		
Soy Demand dt × L. Firm Exports		0.052*		
		(0.028)		
Soy Demand dt × L.GDP per cap.			-0.025	-0.004
			(0.022)	(0.020)
Soy Demand dt × Distance to Port			0.033	
			(0.022)	
Soy Demand dt × L.Deforesta. (Mapbiomas)				-0.006***
				(0.002)
Constant	-25.246***	-23.010*	15.316***	17.267***
	(9.614)	(12.971)	(3.791)	(3.181)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	ct dt	ct dt	ct dt	ct dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.10: Placebo: other-than-soy exports

	Dep. Variable: Firm-level Exports Values			
	(1)	(2)	(3)	(4)
Other-than-soy Demand	0.000	0.109		
	(0.028)	(0.455)		
Other-than-soy Demand × L. Firm Exports		-0.006		
		(0.022)		
Other-than-soy Demand × L.GDP per cap.			-0.024*	-0.008
			(0.015)	(0.014)
Other-than-soy Demand × Distance to Port			0.019	
			(0.017)	
Other-than-soy Demand × L.Deforesta. (Mapbiomas)				-0.006***
				(0.001)
Constant	-27.937***	-21.206*	17.248***	17.742***
	(9.436)	(12.456)	(2.853)	(2.138)
Observations	58925	26252	31830	31830
R^2				
Fixed Effects	fcd fct	fcd fct	fdt fct	fdt fct
Controls: Dest-Year	yes	yes		
Cluster Level	dt	dt	dt	dt

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Bibliography

Abman, Ryan and Clark Lundberg, "Does Free Trade Increase Deforestation? The Effects of Regional Trade Agreements," *Journal of the Association of Environmental and Resource Economists*, 08 2019, *7.*

Assunção, Juliano, Clarissa Gandour, Romero Rocha, and Rudi Rocha, "The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon," *The Economic Journal*, February 2020, *130* (626), 290–330.

Balboni, Clare, Aaron Berman, Robin Burgess, and Benjamin A. Olken, "The Economics of Tropical Deforestation," 2022.

Busch, Jonah, Oyut Amarjargal, Farzad Taheripour, Kemen Austin, Rizki Siregar, Kellee Koenig, and Thomas Hertel, "Effects of demand-side restrictions on high-deforestation palm oil in Europe on deforestation and emissions in Indonesia," *Environmental Research Letters*, 01 2022, *17.*

Defries, Ruth, Thomas Rudel, María Uriarte, and Matthew Hansen, "Deforestation Drive by Urban Population Growth and Agricultural Trade in the Twenty-First Century," *Nature Geoscience - NAT GEOSCI*, 02 2010, *3*, 178–181.

Domínguez-Iino, Tomás, "Efficiency and Redistribution in Environmental Policy: An Equilibrium Analysis of Agricultural Supply Chains," *Princeton University - Department of Economics*, 2022.

Gaulier, Guillaume and Soledad Zignago, "BACI: International Trade Database at the Product-Level. The 1994-2007 Version," Working Paper, CEPII research center October 2010.

Godar, Javier, "Supply chain mapping in Trase. Summary of data and methods," 2018. Publisher: Unpublished.

Harstad, Bard, "Trade, Trees, and Contingent Trade Agreements," *SSRN Electronic Journal*, 2022.

Heilmayr, Robert, Lisa L. Rausch, Jacob Munger, and Holly K. Gibbs, "Brazil's Amazon Soy Moratorium reduced deforestation," *Nature Food*, December 2020, *1* (12), 801–810.

Jia, Fu, Sujie Peng, Jonathan Green, Lenny Koh, and Xiaowei Chen, "Soybean Supply Chain Management and Sustainability:A Systematic Literature Review," *Journal of Cleaner Production*, 05 2020, *255*, 120254.

Melitz, Marc, *International Trade and Heterogeneous Firms* 01

Pendrill, Florence, U Persson, Javier Godar, and Thomas Kastner, "Deforestation displaced: Trade in forest-risk commodities and the prospects for a global forest transition," *Environmental Research Letters*, 05 2019, *14.*

Rausch, Lisa L., Holly K. Gibbs, Ian Schelly, Amintas Brandão, Douglas C. Morton, Arnaldo Carneiro Filho, Bernardo Strassburg, Nathalie Walker, Praveen Noojipady, Paulo Barreto, and Daniel Meyer, "Soy expansion in Brazil's Cerrado," *Conservation Letters*, November 2019, *12* (6).

Santos Silva, J. M. C. and Silvana Tenreyro, "The Log of Gravity," *The Review of Economics and Statistics*, November 2006, *88* (4), 641–658.

Song, Xiao-Peng, Matthew C. Hansen, Peter Potapov, Bernard Adusei, Jeffrey Pickering, Marcos Adami, Andre Lima, Viviana Zalles, Stephen V. Stehman, Carlos M. Di Bella, Maria C. Conde, Esteban J. Copati, Lucas B. Fernandes, Andres Hernandez-Serna, Samuel M. Jantz, Amy H. Pickens, Svetlana Turubanova, and Alexandra Tyukavina, "Massive soybean expansion in South America since 2000 and implications for conservation," *Nature Sustainability*, June 2021.

Souza, Carlos M. and Tasso Azevedo, "MapBiomas General "Handbook"," 2017. Publisher: Unpublished.

Villoria, Nelson, Rachael Garrett, Florian Gollnow, and Kimberly Carlson, "Leakage does not fully offset soy supply-chain efforts to reduce deforestation in Brazil," *Nature Communications*, 09 2022, *13.*

West, Christopher David, Jonathan Michael Halsey Green, and Simon Croft, "Trase Yearbook 2018: Sustainability in forest-risk supply chains: Spotlight on Brazilian soy," 2018.