Foreign Demand, Export Sales, and Deforestation: A Commodity-Level Analysis[1]

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Abstract

Our study quantifies how strongly international demand for agricultural commodities causes deforestation across regions, filling an important empirical gap of commodity-level deforestation study. Using a global country-commodity-year panel (138 countries, 18 commodity groups, 2001-2022), we estimate elasticities of commodity-level deforestation with respect to two representations of international demand: a shift-share style foreign demand and export sales. The main challenge is simultaneity: demand, exports, and deforestation are jointly determined. We address this by constructing a foreign-demand variable that leverages plausibly exogenous demand of product in destination markets. We find that the stronger international demand causes significantly higher deforestation. The effects are largest for land-intensive perennial commodities, such as rubber, palm, cocoa, nuts, and coffee. Other important commodity groups are soybeans, cattle, and sugar crops. We found that most of the effects are concentrated in South America, Southeast Asia, and to some extent in Africa. Back-of-the-envelope calculations suggest that increases in international demand account for approximately 28 to 41 million hectares of agricultural expansion into forests between 2001 and 2022, which is 25 to 37% of forest-to-agriculture conversion. Our elasticities can serve as behavioral parameters for modelers who want to connect trade models with deforestation outcome to conduct policy experiments of trade-linked environmental regulations or policies.

JEL-Codes: Q17, Q56, F18

Keywords: Deforestation, Foreign Demand, Export sales, PPML, Shift-share

[1] This is my second job market paper. Preprint. Comments are welcome. All errors are my own.

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1 Background

Agriculture expansion is a significant driver of tropical deforestation, that directly poses socio-economic and ecological challenges. A large share of global diversity resides in tropical forests, and the loss of these forests directly causes significant biodiversity decline (Giam 2017; Alroy 2017). Further, deforestation intensifies the warming and drying effect (for e.g., Lee and Lo 2021) and changes rainfall pattern (for e.g., Lee and Lo 2021; Werth and Avissar 2005), which can directly affect agricultural productivity (Lawrence and Vandecar 2015). These climatic impacts are not limited to deforesting regions. Through eco-climate teleconnections, distant locations also face climate and hydrological changes due to forest loss (e.g., Snyder 2010; Garcia et al. 2016; Serrão et al. 2025). Many human health problems are associated with deforestation, including increased respiratory and cardiovascular problems (Damm et al. 2024; Du, Li and Zou 2024) and higher malaria incidence (Chaves et al. 2020; Arisco et al. 2024; Berazneva and Byker 2017). These externalities of deforestation underscore the importance of understanding drivers of tropical deforestation.

A major driver of deforestation is international demand for agricultural commodities. Pendrill, Persson, Godar, Kastner, Moran, et al. (2019) and Pendrill, Persson, Godar and Kastner (2019) estimate that international agricultural trade accounts for roughly one-third of tropical deforestation. Commodities, such as cattle, soy, oil palm, cocoa, coffee, and rubber, accounts for much of the deforestation embodied in trade, with hotspots in South America, Southeast Asia, and parts of Africa (Zu Ermgassen et al. 2020; Pendrill, Persson, Godar and Kastner 2019; Singh and Persson 2024; Goldman et al. 2020). However, most of these literature either relies on accounting frameworks that trace embodied deforestation through supply chains (e.g., Zu Ermgassen et al. 2020; Pendrill, Persson, Godar and Kastner 2019; Singh and Persson 2024) or examines broad aggregate relationships, such as trade liberalization and forest loss (Abman and Lundberg 2020; Farrokhi et al. 2025) or commodity prices and deforestation (Berman et al. 2023; Lundberg and Abman 2021; Harding, Herzberg and Kuralbayeva 2021). Understanding of how strongly international demand causes deforestation at the commodity and regional levels remains understudied. Existing causal studies focus on particular hotspots—most notably Brazil, Indonesia or some African countries—given data limitations and the complexity of global supply chains (e.g., Du et al. 2024). Many factors, such as trade policies, prices, governance, drive deforestation directly, including indirect deforestation through production displacement across regions and crops, complicating identification of commodity-specific effects. Understanding the elasticity of deforestation with respect to international demand is particularly important as populations and incomes grow in developing countries and as trade liberalization alone may have limited effects on global forest area (Farrokhi et al. 2025).

In this paper, we advance the analysis to a broader set of commodities and continents, providing commodity- and region-specific causal estimates of demand-driven deforestation.

We measure international demand in two ways. First, we use export sales, representing country-level export demand by commodity. Second, we construct a plausibly exogenous foreign-demand shifter using a shift–share design: a weighted average of supply-corrected imports by destination countries, where weights are given by fixed export shares. We compile a panel of deforestation attributed to 18 agricultural commodities for 138 countries over 2001–2022. To address endogeneity arising from the joint determination of exports and deforestation (e.g., Burgess et al. 2012; Burgess, Costa and Olken 2019; Abman and Lundberg 2020; Balboni et al. 2022; Harstad 2024), we use foreign demand as an instrument for export demand to estimate the effect of export sales on deforestation in a control-function PPML framework. Intuitively, the exposure-weighted foreign-demand index aggregates destination–product import growth that is orthogonal to a given country's own supply shocks. We saturate the specification with country–year fixed effects to absorb governance and national policy shocks that vary over time, and with commodity–year fixed effects to net out global sectoral shocks such as prices, technologies, or consumer preferences. Because many country–commodity–year cells exhibit zero forest conversion, we estimate Poisson pseudo-maximum likelihood models, which accommodate zeros and yield elasticities with tractable interpretation.

We find that increases in international demand leads to significant increases in commodity-attributed deforestation, with strong heterogeneity across commodities and regions. The deforestation elasticities to international demand are largest for land-intensive perennial commodities, such as stimulants and spices, rubber, oil palm, cocoa, nuts, coffee, sugar crops, including soybeans, and cattle. The staple and horticultural crops exhibit much weaker responses. We suggest three potential explanation for these patterns. First, these commodities involve high fixed costs of establishment but relatively low marginal costs of expanding onto nearby forest land. So demand shocks are met mainly through expansion. Second, they are high-value export-oriented commodities, making frontier conversion privately profitable even under substantial transport and clearing costs. Third, their agro-climatic suitability overlaps strongly with humid tropical forest frontiers, such as South America, Southeast Asia, and to some extent in Africa. Back-of-the-envelope calculations indicate that growth in international demand can account for roughly 28–41 million hectares of agricultural expansion into forests between 2001 and 2022, corresponding to about 25–37% of observed forest-to-agriculture conversion.

This paper makes three main contributions. First, it provides global, commodity-level causal estimates of how international demand affects deforestation, complementing and extending recent work on trade–deforestation linkages that has largely focused on single countries or a narrow set of commodities (e.g., Harstad 2024; Farrokhi et al. 2025; Berman et al. 2021; Du et al. 2024). By integrating newly available product-attributed deforestation data with bilateral trade flows, we deliver directly comparable elasticities across 18 commodity groups over 2001–2022. Second, the resulting elasticities can serve as behavioral parameters for quantitative trade and land-use models, enabling ex-ante policy simulations of trade-linked environmental regulations, such as the European Union Deforestation Regulation. Third, our results inform the design of anti-deforestation governance by quantifying where and for which commodities export demand translates most strongly into land expansion and forest loss, thereby helping to prioritize monitoring, traceability, and enforcement efforts, and to balance environmental and trade objectives at the commodity- and continent-specific level.

2 Conceptual framework: The effects of foreign demand and export sales on deforestation

The causal diagram, as shown in figure 1, illustrates the transmission of foreign demand effect on deforestation through three mediated channels. First, higher international demand increases international prices (α), the higher international prices translate into higher exports (β), and expanding exports demand drive deforestation (γ) when the marginal land supply is forest. This "price-to-deforestation" channel underpins much of the theoretical and empirical literature that links crop prices to forest loss in tropical frontiers (e.g., Berman et al. 2021; Bragança 2018; Wilcox, Just and Ortiz-Bobea 2025; Lundberg and Abman 2021). It is also consistent with structural trade models where changes in world prices reallocate land across sectors and regions (e.g., Farrokhi et al. 2025). Second, international demand can also increase exports directly, (θ), even holding prices constant. Examples include forward contracts, investment in processing capacity and bilateral agreements that are tied to foreign buyers. Third, international price can drive deforestation δ directly through domestic price pass-through, land speculation, or weakening governance enforcement. The multinational firms operationalize this mechanism by scaling procurement and logistics when international prices goes up, linking global demand to local production, and ultimately incentivizing forest conversion. Evidence from Brazil and Cambodia shows that commodity prices and staple-food price spikes can alter deforestation independently of export volumes, especially where governance is weak or enforcement is pro-cyclical (Assunção, Gandour and Rocha 2015; Harding et al. 2021; Wilcox et al. 2025). Taken together, the total effect of foreign demand on deforestation are through price and non-price (i.e., exports) paths, $(\alpha\beta\gamma + \theta\gamma + \alpha\delta)$. However, there can be feedback loops as well: deforestation can drive exports, exports can drive international price and international price drives foreign demand. If we can control international price and domestic shocks, the effect of international demand on deforestation remains only through exports, i.e., $\theta\gamma$.

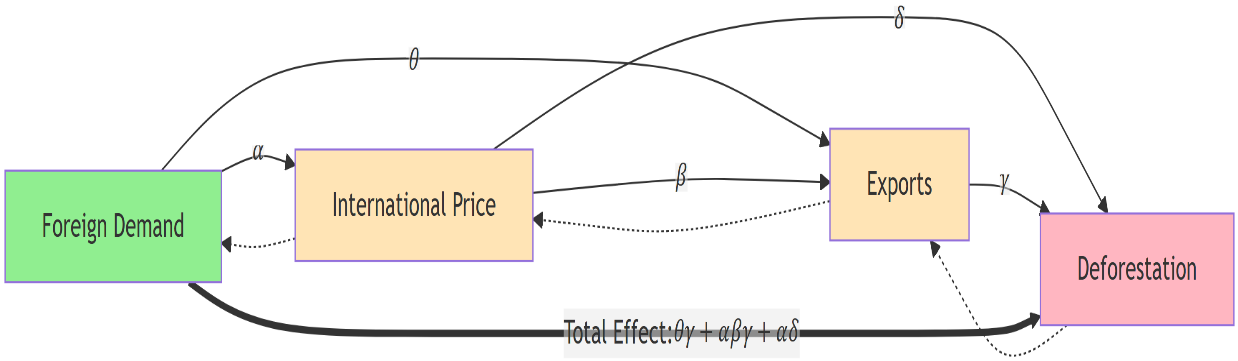


Figure 1: Causal diagram between foreign demand, exports and deforestation

Source: Own illustration

Under competitive market, producers expand land use until marginal value product of land, $(MVPL)$, equals rental value (R), as shown in figure 2. A positive demand shock abroad that raises output prices shifts the $MVPL$ rightward. The profit-maximizing land allocation increases from L_1 to L_2. If the available margin of land supply is forest, deforestation rises and export rises. The optimal allocation of land across commodities depends on their relative $MVPLs$. In many settings, the marginal returns to agricultural commodities exceed those from forestry, contributing to high deforestation in the tropics (Benhin 2006). This decision is individually rational yet not socially optimal, because markets fail to price the full social benefits of forests. Beyond price movements, anticipatory dynamics also matter: expectations of persistently higher export prices may induce speculative clearing before demand fully materializes.

This simple diagram formalizes the mechanism emphasized by many empirical studies: commodity-specific price shocks induce changes in land allocation at the forest margin. Using a global crop-price index interacted with agro-climatic suitability, Berman et al. (2021) shows that price shocks generate the largest deforestation where suitable forest and market access are abundant. Commodity- and country-specific studies similarly find that higher relative returns to soy vs cattle (Bragança 2018), rice vs other crops (Wilcox et al. 2025), or cocoa vs staples (Krah 2021; Renier et al. 2025) shift land into the more profitable activity, often at the expense of forests. Our framework nests these mechanisms: international demand affects returns either by raising prices or by increasing export opportunities for particular commodities, and land reallocation at the frontier converts forests into cropland or pasture.

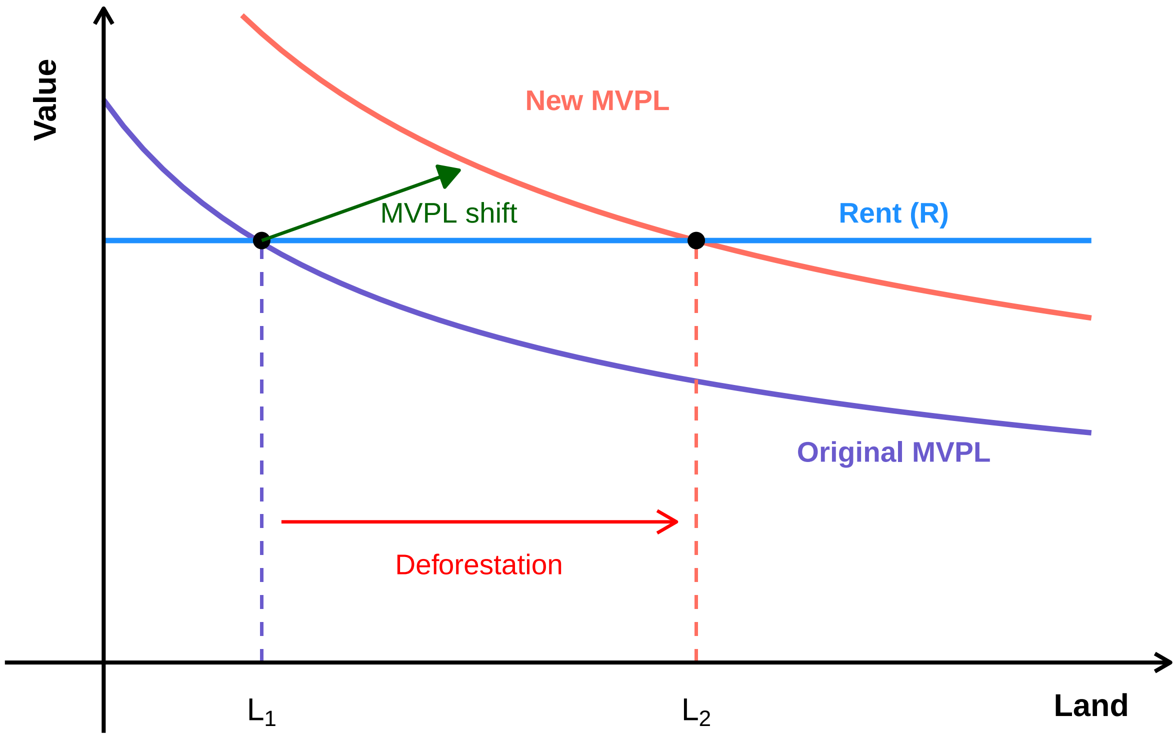


Figure 2: Shift in the marginal product value of land resulting from increase in price due to higher foreign demand

Source: Own illustration

Macro and cross-country evidence is broadly consistent with the mechanisms discussed in aforementioned paragraphs. The macro and cross-country literature is broadly consistent with this conceptual framework. Studies that relate forest loss to income or trade—often through Environmental Kuznets-type hypotheses—find that deforestation accelerates during early stages of development and export expansion, particularly in land-abundant, low-governance settings (e.g., Culas 2007; Caravaggio 2020; Ajanaku and Collins 2021). Structural counterfactual analyses confirm that international demand and trade policy shape land outcomes: removing tariffs on forest-risk products increases deforestation, while restricting exports of illegal wood reduces it (Beckman et al. 2017). Dynamic trade models suggest that multilateral liberalization can lead to modest global forest gains via structural change, but with substantial heterogeneity—countries with strong agricultural comparative advantage, such as Brazil, tend to lose forest, while others reforest (Farrokhi et al. 2025).

Country- and commodity-level studies provide more detailed micro-foundations for our channels. In Brazil, a large body of work documents how soy and cattle prices, interacting with governance and infrastructure, drive both direct and indirect deforestation (Assunção et al. 2015; Harding et al. 2021; Bragança 2018; Hargrave and Kis-Katos 2013; Arima et al. 2011). For Cambodia and Ghana, rising or volatile staple prices can induce producers to expand into higher-value cash or export crops, increasing forest loss (Wilcox et al. 2025; Krah 2021; Lundberg and Abman 2021). Global attribution studies trace the share of forest loss embodied in specific commodities and trade flows, highlighting cattle, soy, palm oil, wood fiber, cocoa, coffee, and rubber as key drivers (Goldman et al. 2020; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019; Zu Ermgassen et al. 2020; Renier et al. 2025).

Institutions and policy repeatedly emerge as critical moderators of these relationships. Weak land rights, corruption, and politically driven enforcement cycles amplify the translation of trade shocks into deforestation (Burgess et al. 2012; Burgess et al. 2019; Cisneros, Kis-Katos and Nuryartono 2021). Trade agreements can further increase forest pressure in countries with comparative advantage in agriculture (Abman and Lundberg 2020), motivating the recent shift toward trade-linked environmental regulations such as the EU Deforestation Regulation and contingent trade agreements (European Parliament and of the Council 2023; Harstad 2024). Finally, the structure of global supply chains—dominated by a few large multinational buyers—can accelerate procurement responses to demand shocks and alter the local incidence of rents and land-use decisions (Crepin and Nedoncelle 2023; Nedoncelle, Delacote and Crepin 2025).

Against this backdrop, our framework emphasizes the export-mediated path of international-demand growth, while acknowledging that price and institutional channels are integral to the broader system. Existing studies provide strong support for each individual path in our diagram, but typically focus on a subset of crops, countries, or mechanisms. By combining international demands, export sales, and spatially explicit deforestation for a broad set of commodities and countries, our study provides a comprehensive view of how international demand transfers through export sales into forest loss, and how this process varies across commodities and continents. Understanding this heterogeneity is particularly important given rising food and commodity demand in developing countries and the rapid emergence of trade-linked deforestation regulations.

3 Data and empirical strategy

3.1 Data

Our dataset covers 138 countries (listed in appendix 1) and 18 commodity groups comprising 493 products defined at the Harmonized System (HS) level, between the period 2001 and 2022. We select only countries that experienced agricultural-driven deforestation in all 22 years. The correspondence of HS codes to 18 commodity groups is shown in appendix 2. The unit of observation in our dataset is a country-commodity-year triplet. The panel is unbalanced, since not all countries produce all commodities because production depends on climatic suitability. We removed out 483 unrealistic country-commodity pairs out of possible pairs ($138 \times 18 = 2484$) , leading to 2001 country-commodity pairs. We purposefully selected only those pairs (i.e. 2001) which are consistently reported in the BACI trade database. For example, tropical commodities such as rubber, coffee, cocoa and cassava, are not paired with any European countries over the study period (see appendix 10 to understand panel structure).

Deforestation. We obtain commodity-attributed deforestation estimates from the DeDuce model developed by Singh and Persson (2024), which allocates forest loss across countries and commodities defined by FAOSTAT item names. The model reports both unamortized and amortized deforestation (see appendix 3 for model details). Unamortized deforestation represents the immediate, full accounting of forest loss in the year it occurs, while amortized deforestation distributes the consequences, particularly carbon emissions, across multiple years using a 5-year amortization period (rather than the typical 20-year IPCC standard) to capture more immediate policy relevance. We use unamortized deforestation data for our study. Figure A3.1 illustrates the accumulated deforestation for each country during the sample period. We aggregate FAOSTAT commodity-level deforestation into 18 groups: cassava, cocoa, coffee, fibre crops, fruits, maize, nuts, other cereals, other oilseeds, cattle (pasture), pulses and legumes, rice, rubber, soybeans, stimulants/spices/aromatics, sugar crops, and vegetables. The correspondence of FAOSTAT items to these 18 groups is shown in appendix 4.

Trade: We utilize the CEPII-BACI trade matrix, which contains the trade flows in HS of classification of products. We rely on BACI trade matrix because it is more reliable than raw data from Comtrade as it reconciles mirror figures to address discrepancies and improve accuracy (Gaulier and Zignago 2010). We match HS codes to our 18 commodity groups to construct country–commodity–year export values and quantities.

3.2 Empirical strategy

Our objective is to estimate how changes in international demand affect deforestation at the country-commodity level. Let i index countries, k commodities, and t years. Our baseline specification that related deforestation C_{ikt}, to export sales, X_{ikt}, while absorbing rich-time varying confounders with country-year α_{it} and commodity-year fixed effects α_{kt} is:

$$C_{ikt} = \gamma \log X_{ikt} + \alpha_{it} + \alpha_{kt} + \varepsilon_{ikt}. \qquad (1)$$

Since our dataset has many zero-deforestation observations as shown in table 1, taking logarithmic transformation excludes those observations. To take account of zero, we estimate the conditional mean with Pseudo Poisson Maximum Likelihood (PPML), which preserves zero and is robust to heteroskedasticity. For comparisons and sensitivity checks, we report the Ordinary Least Square (OLS) estimator on the level, logarithmic and inverse hyperbolic sine (IHS) specification. However, we emphasize PPML because it delivers interpretable elasticities without transformation bias (Bellemare and Wichman 2020; Mullahy and Norton 2024).

The unbiased estimation the effect of export sales on deforestation faces two main challenges. First, simultaneity between exports and deforestation: expanding agricultural land directly increases a country's capacity to export, and unobserved shocks (e.g., new roads, changes in enforcement) may jointly raise both exports and forest clearing. Second, there is a backdoor path through international prices: global demand shocks influence deforestation via prices even if measured exports are constant.

To address these concerns, we follow the shift–share literature (e.g., Borusyak, Hull and Jaravel 2022) and construct an exogenous foreign-demand variable for each country–commodity pair. This measure interacts predetermined export shares with import growth in destination–product markets that is plausibly orthogonal to contemporaneous country-specific shocks. In the first stage, we predict export sales using foreign demand. In the second stage, we estimate the effect of these instrumented exports on deforestation. We use commodity-year fixed effects to absorb international price shocks, while country-year fixed effects absorb domestic policy changes, macroeconomic conditions, and common supply shocks.

A key question is how much to control for comparative advantage. Country–commodity fixed effects capture time-invariant geography, long-run agro-climatic suitability, and persistent institutional features. These factors plausibly shape both export potential and baseline forest cover, and thus the exposure of forests to trade shocks. However, conditioning on them too aggressively can be counter-productive. If comparative advantage operates largely by enabling export-driven land expansion, then controlling for country–commodity dummies risks "soaking up" the very variation that links shifts in foreign demand to changes in land use—akin to conditioning on a mediator or collider. Moreover, forests themselves can create comparative advantage by acting as a store of fertility or as land reserves that facilitate future expansion (Benhin 2006). For these reasons, our baseline specifications use country-year and commodity-year fixed effects, while allowing variation in country-commodity pairs to mediate the response to international-demand shocks.

Formally, we construct the instrumental variable (IV), namely foreign demand (FD_{ikt}), to export sales of commodity k of country i at year t. This approach closely follows the exogeneous shift-based method outlined by Borusyak, Hull and Jaravel (2024). In our context, the ideal exogenous treatment are foreign demands for product-destination pair, $(s \times j)$, proxied by log of supply-corrected imports by foreign countries $\log(Import^{k}_{jst})$, where s represents products and j represents foreign countries, such that $s \in k$[3]. We employ the multiplicative gravity model to estimate supply-corrected imports as below.

$$X_{ijst} = \exp(\gamma_{ist} + \gamma_{jst} + \gamma_{ijs})\varepsilon_{ijst}, \qquad (2)$$

where, X_{ijst} is bilateral trade between countries i and j of product s at year t, γ_{ist} is exporter-product-year fixed effect, γ_{jst} is importer-product-year fixed effect and γ_{ijs} is country-pair-product fixed effect. The exporter-product–time fixed effects capture product output and outward multilateral resistance terms, whereas country-pair-product fixed effects include time invariant pair- and product-specific trade policies and trade costs. The exporter's supply price is embedded in both the product-output and outward multilateral resistance terms. Therefore, supply-corrected imports effectively remove exporter-side supply shocks, including changes in exporters' supply, prices, and policies, and isolate importer–product demand factors. The supply corrected imports is given by,

$$\log(Import_{jst}) = \log\left(\sum_{i} \frac{X_{ijst}}{\exp(\gamma_{ist} + \gamma_{ijs})}\right). \qquad (3)$$

We treat importer–product–year demand shocks as exogenous to deforestation in country–commodity (i, k), since they reflect destination-side income fluctuations, preference shifts, sector-specific policies, and supply disruptions outside country i. Reverse causality is implausible in the short run, because deforestation in i cannot systematically change foreign consumers' product-level demand across many destinations. To further mitigate reverse causality, we use one-year lags of importer–product–year demand, as shown in equation (5).

The share used in our shift-share IV is the importance of product-destination (j, s) in the export portfolio of commodity k of country i at year t, calculated at its share in the country's total commodity exports during the period 2001-2022. These pre-determined shares, which is sum to one

[3] Our foreign demand exclude destination countries' domestic sales. While part of a destination's demand growth may be met by its own production, we assume that land and production constraints imply that a meaningful portion of demand growth is transmitted internationally via trade, which is what our instrument captures.

within $i \times k$, are combined with time-varying supply-corrected imports to form the foreign demand measure. One may raise concern that time-invariant variation may also come from fixed product-destination exposures within a commodity-country pair. However, we report on exposure concentration using Herfindahl-Hirschman index for each commodity in appendix 5 to support "many small shocks" conditions standard in the shift-share literature. Formally, the share is defined as:

$$\omega^k_{ijs,2001-2022} = \frac{X^k_{ijs,2001-2022}}{X^k_{i,2001-2022}}. \qquad (4)$$

The foreign demand is then expressed as:

$$FD_{ikt} = \sum_j \sum_s \omega^k_{ijs,2001-2022}(\log(Import^k_{js,t-1})). \qquad (5)$$

Technically, a 1% increase in imports of each product-destination pair (s, j) corresponds to about a 0.01 increase in FD of country-commodity pair, (i, k), which is equivalently 1% increase in FD. Therefore the direct effect of foreign demand faced by country is also the parameter of our interest. We estimate the direct effect of international demand using the PPML reduced form, as shown below.

$$C_{ikt} = \exp(\beta FD_{ikt} + \beta_{it} + \beta_{kt})\varepsilon_{ikt}, \qquad (6)$$

where, the coefficient β can therefore be interpreted as the elasticity of deforestation with respect to foreign demand: a 1% increase in international demand for commodity k faced by country i leads to an approximate β % change in expected deforestation.

Further, in the gravity setting, the importer-product-year fixed effects, γ_{jst}, capture importers' expenditures on imports and so-called "inward multilateral resistance"[4]. This term is exogenous to exports and deforestation and represents the conservative variant of foreign demand. We therefore also consider an IV constructed directly from these predicted fixed effects.

$$\widehat{FD_{ikt}} = \sum_j \sum_s \omega^k_{ijs,2001-2022}(\widehat{\gamma^k_{js,t-1}})). \qquad (7)$$

The relevancy of FD_{itk} to explain the exports sales are shown in appendix 7, which are significant. We also check for sub-samples of commodities and continents, which are also consistently significant. The effect of FD_{ikt} on export sales are positive while $\widehat{FD_{ikt}}$ are negative, which makes sense. The FD_{ikt} is a representation of international demand. However, the $\widehat{FD_{ikt}}$ is an aggregation of destination-product-year fixed effects that incorporates so-called "inward mul-

[4]It captures how difficult it is for importers to import products from suppliers.

tilateral resistance" term. In other words, it is an aggregation of a CES price index of the cost of accessing products from exporters. The higher price index for country j means harder for the country i to export to country j. We include country-year fixed effects to control common domestic confounders and commodity-year fixed effects to control commodity-specific global shocks, particularly international price shocks.

With FD_{ikt} and $\widehat{FD_{ikt}}$ as instruments, we estimate the causal effect of export sales on deforestation in a nonlinear framework. Our specification employs a control function (two-stage residual inclusion) estimator within a Poisson pseudo–maximum likelihood (PPML) model. In nonlinear mean models such as PPML, replacing the endogenous regressor with its first-stage fitted values generally yields inconsistent partial effects while residual inclusion via a control function restores consistency under standard conditions (Wooldridge 2015; Papke and Wooldridge 2008). In the first stage, we estimate a linear reduced-form for exports with fixed effects and obtain the residuals:

$$\log X_{ikt} = \pi FD_{ikt} + \alpha_{it} + \alpha_{kt} + \nu_{ikt}, \qquad (8)$$

where α_{it} are country-year fixed effects, and α_{kt} are commodity-year fixed effects. We estimate this equation by fixed-effects OLS and recover the control-function residuals, $\hat{\nu}_{ikt}$. In the second stage, we employ PPML that includes both the endogenous regressor and the first-stage residual (two-stage residual inclusion):

$$\mathbb{E}\left[C_{ikt} \mid \log X_{ikt}, \alpha_{it}, \alpha_{kt}, \hat{v}_{ikt}\right] = \exp\left(\alpha \log X_{ikt} + \alpha_{it} + \alpha_{kt} + \delta\hat{\nu}_{ikt}\right). \qquad (9)$$

Our baseline takes $h(\nu_{ikt}) = \delta\hat{\nu}_{ikt}$ (linear residual inclusion). By construction, this CF-PPML estimator preserves observations with $C_{ikt} = 0$ and is robust to heteroskedasticity provided the conditional mean is correctly specified. Under these conditions, α identifies the elasticity of deforestation with respect to exports in the PPML log-link: $\frac{\partial ln[C_{ikt}|.]}{\partial ln X_{ikt}} = \alpha$. Thus, for a 1 percent change in exports, the proportional change in the conditional mean of deforestation is approximately α percent. For inference, the second stage contains a fitted regressor $\hat{\nu}_{ikt}$, so naive standard errors can be anti-conservative. We report a non-parametric block bootstrap standard errors that resample at the country-commodity level and recompute both stages in each replication. All reported p-values and confidence intervals are based on this bootstrap percentiles. A Smith–Blundell–type endogeneity test, $H_0 : \delta = 0$, in the second stage, provides a formal check for whether residual inclusion is warranted. The bootstrap procedure is discussed in the appendix 9.

3.3 Descriptive Statistics

The dataset includes 41,829 country-commodity-year observations. Table 1 reports the descriptive statistics of deforestation (ha), export ('000 USD) and foreign demand. Deforestation is highly skewed, with an average of 3,028.43 hectares (median 5.82 ha) and a standard deviation of 40,598.88 hectares. A total of 8158 country-commodity-year observations are zero. Export sales are also skewed, with a mean of 393,786.25 ('000 USD), median 15,089.70 ('000 USD), and a long right tail with maximum of 62,644,370.49 thousands USD. The average foreign demand is 7.72 (median 8.72) and falls between 0 and 17.68. The foreign demand is actually the aggregation of product demands across destination–which is over 6.9 millions observations between 2001 and 2021)–based on their export shares (over 2.1 millions observations) in country-commodity pairs. The descriptive statistics of shares and shifts are reported in appendix 5 and appendix 6, respectively.

Table 1: Descriptive statistics of variables under study

Statistic	Export ('000 USD)	Deforestation (ha)	Foreign Demand	$\widehat{FD}$
Count of Zero	0.00	8,157.00	0.00	0.00
Minimum	0.00	0.00	0.00	-10.02
Mean	393,410.02	2,671.73	12.53	-0.48
Maximum	62,644,370.49	2,467,977.22	29.61	9.58
1st Quartile	895.32	0.00	6.92	-0.85
Median	15,051.39	5.82	14.14	-0.36
3rd Quartile	132,639.35	180.80	18.31	-0.02
Standard Deviation	1,625,887.95	38,071.88	6.97	0.74

Figure 3 illustrates the relationship between deforestation, foreign demand, and exports. Panel (a) indicates that commodities with higher export growth tend to have higher cumulative deforestation. Commodities with notable higher export growth includes other oilseeds (1,139%), palm (1,137%), cassava (1,028%), soybeans (557%), and maize (493%). However, cattle has very high cumulative deforestation footprint with moderate export growth (394%). Panel (b) indicates that several commodities have disproportionate deforestation share relative to export share. Commodities such as cattle , cassava, palm, rubber, rice, pulses, cocoa, and maize have higher deforestation share in relative to export share. Conversely, fruits, other cereals, vegetables, sugar, stimulants, coffee, other oilseeds, nuts, and soybeans has lower deforestation share in relative to their export share. Panel (c) underscore that commodities varies starkly in deforestation intensity, as measured in hectares per $1 billion of export sales. The intensity is highest for cassava (~66 ha per $1 billion export sales) and cattle (~31), followed by palm (~19) and rubber (~15). A middle tier includes pulses (~11.9), rice (~10.4), cocoa (~9.8), and maize (~8.8). Export categories with low intensity include other cereals (~1.0), fruits (~1.35), vegetables (~1.78), sugar (~1.80), and nuts (~1.97). Panel (d) indicates that correlation matrix. The correlations are statistically significant, but relatively weak for deforestation-exports (correlation coefficient: 0.20) and deforestation-foreign demand (correlation coefficient: 0.05), while the foreign demand-exports relationship is strong.

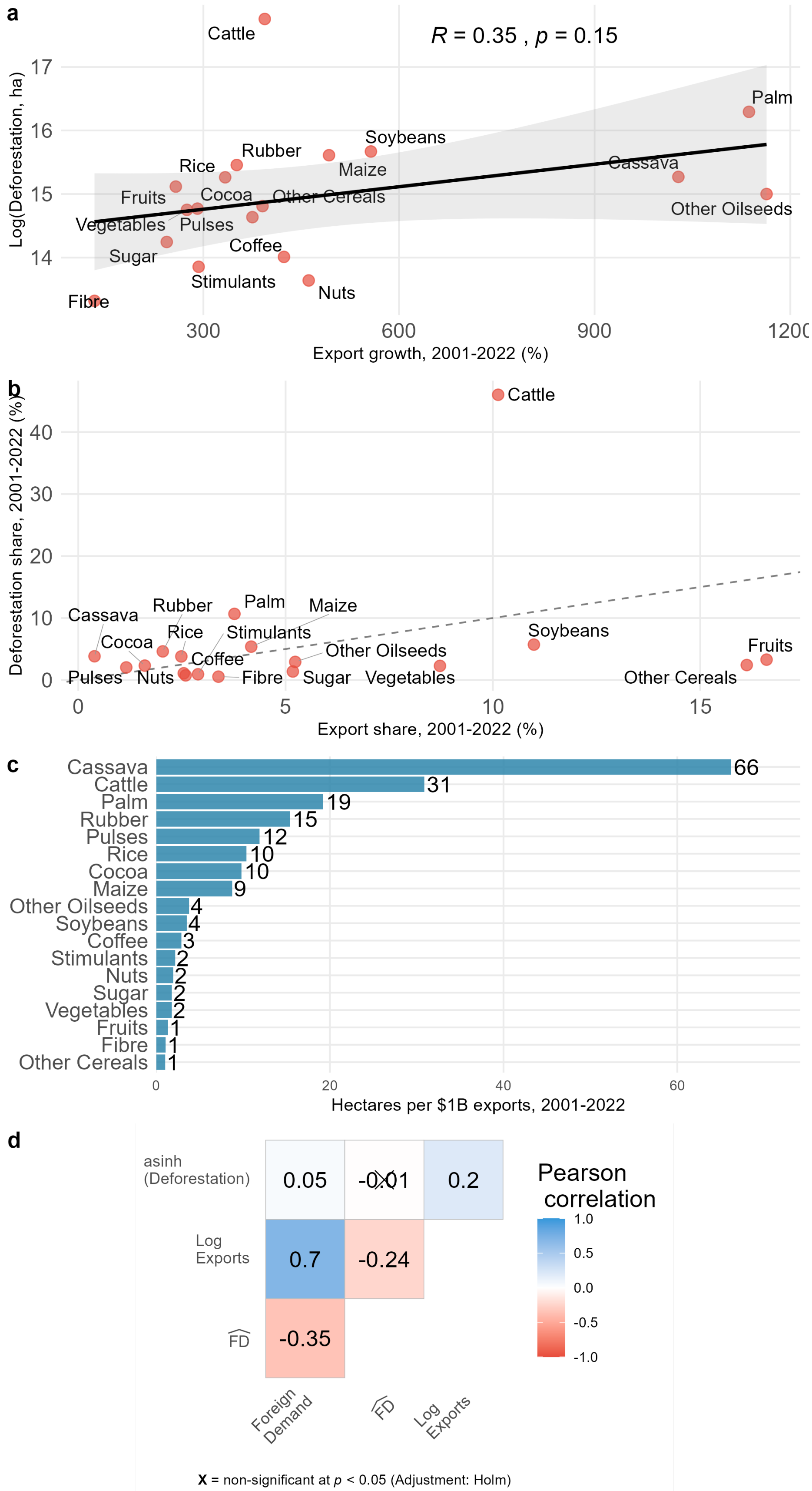

a
R = 0.35 , p = 0.15
Log(Deforestation, ha)
Export growth, 2001-2022 (%)
Cattle
Palm
Soybeans
Rubber
Maize
Cassava
Rice
Fruits
Cocoa
Other Cereals
Other Oilseeds
Vegetables
Pulses
Coffee
Sugar
Stimulants
Nuts
Fibre
b
Deforestation share, 2001-2022 (%)
Export share, 2001-2022 (%)
c
Cassava 66
Cattle 31
Palm 19
Rubber 15
Pulses 12
Rice 10
Cocoa 10
Maize 9
Other Oilseeds 4
Soybeans 4
Coffee 3
Stimulants 2
Nuts 2
Sugar 2
Vegetables 2
Fruits 1
Fibre 1
Other Cereals 1
Hectares per $1B exports, 2001-2022
d
asinh (Deforestation)
Log Exports
FD
Foreign Demand
Pearson correlation
X = non-significant at p < 0.05 (Adjustment: Holm)

Figure 3. Relationship between foreign demand, exports, and deforestation. Panel (a) shows log of cumulative deforestation (hectares) against the exports growth over 2001 to 2022 by commodity group. Black solid line represents OLS fitted line and shaded regions denote 95% confidence interval. Panel (b) compares deforestation shares against export share by commodity group. The dashed line is 45 degree line indicating equal share of deforestation and export; Panel (c) shows bar plots of deforestation intensity, measured as hectares per $1 billion of export sales; Panel (d) presents pearson correlation matrix between deforestation, foreign demand and exports. Panels (a)-(c) use commodity-level aggregares; panel (d) uses country-commodity-year data.

4 Results

This section reports the effects of foreign demand and export sales on deforestation agriculture. We present (i) pooled elasticities, (ii) heterogeneous effects across commodities and across continents, and (iii) heterogeneous effects across continent–commodity pairs. We then summarize robustness checks across alternative specifications.

4.1 Effects of foreign demand on deforestation

We examine the causal relationship between foreign demand and deforestation using Poisson pseudo–maximum likelihood (PPML) estimator under four specifications: (i) pooled specification, (ii) heterogeneous effect by commodity group, (iii) heterogeneous effect by continent, and (iv) heterogeneous effect by continent-commodity pairs. The specifications details are in appendix 11.

Table 2 reports the result of the pooled specification, which suggests that higher foreign demand leads to more deforestation. The coefficient on foreign demand is 0.157, indicating that 1% change in foreign demand leads to roughly a 0.157% increase in deforestation associated with agricultural expansion. Our estimated elasticity is substantially smaller than 0.703 effect estimated by Berman et al. (2023). However, the outcome variable used by Berman et al. (2023) is total deforestation and aggregates on only 15 commodities which are reportedly high expanding commodities on forest land.

Table 2: Effect of foreign demand on deforestation

	Pooled
Foreign Demand	0.157***
	(0.038)
Observations	41103
R-squared	0.804
Country × Year FE	Yes
Commodity × Year FE	Yes

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

Note: Standard errors, clustered by country, commodity groups and year, are shown in parenthesis. The specification also includes country–year and commodity–year fixed effects.

Figure 4 illustrates heterogeneous elasticities of deforestation with respect to foreign demand by commodity group (panel a) and by continent (panel b). At the commodity level, the largest positive elasticities are for palm (0.58), cocoa (0.50), and rubber (0.44), all statistically significant. Additional positive and statistically significant responses are observed for cattle (0.19), coffee (0.16), soybeans (0.17), nuts (0.18), other oilseeds (0.12), sugar crops (0.09) and pulses (0.075). Other commodities are not statistically different from zero, which include fibre crops, fruits, maize, rice, stimulants, vegetables, and other cereals. Cassava is significant negative (−0.14). The explanation could be that when countries face increasing international demand for cassava, this is met by either intensification or land reallocation. These patterns are consistent with the idea that land-intensive perennial commodities, such as palm, rubber, cocoa, cattle, coffee, nuts and sugar, account for stronger deforestation response, whereas many staples and horticultural crops have weaker responses (Barbier 2004; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019; Oliveira, Jafari and Börner 2025; Carreira, Costa and Pessoa 2024; Du et al. 2024).

At the continent level, elasticities are largest in South America (0.24) and the Rest of Asia (0.15), followed by North & Central America (0.14), Africa (0.12), Southeast Asia (0.11) and Oceania (0,07). All of these are statistically significant below 10%. The estimates for Europe (0.027) and North Asia (0.015) are statistically insignificant. This pattern mirrors the concentration of deforestation-embodied trade in South American and Southeast Asian exporters and, to a lesser extent, in parts of Africa and the Rest of Asia (Meyfroidt, Rudel and Lambin 2010; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019).

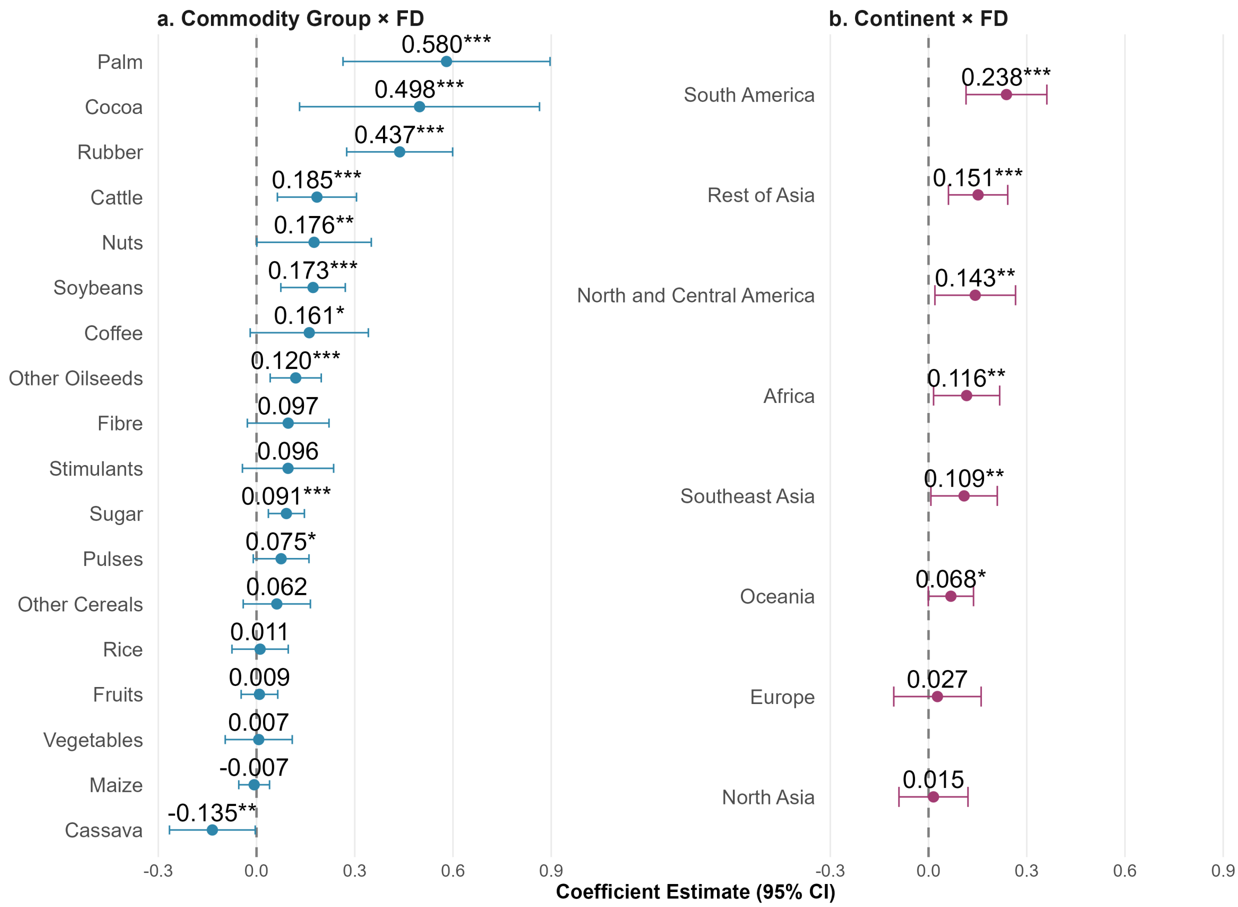


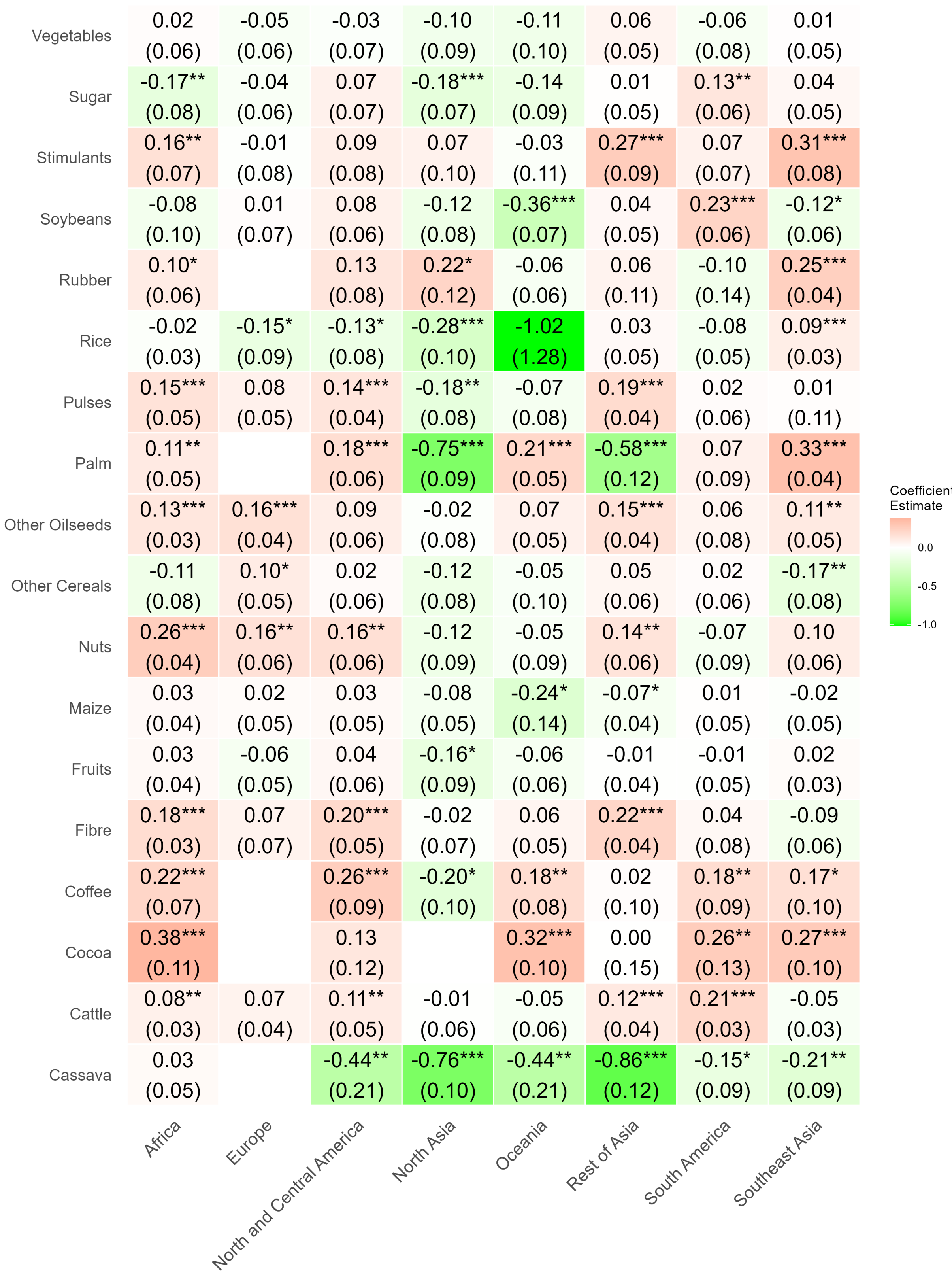
Figure 4: Deforestation elasticities with respect to foreign demand by commodity and continent. The estimates are based on PPML regression. The fixed effects include country-year and commodity-year fixed effect. The standard errors are clustered at country and year levels for panel (a) and clustered at country, commodity and year levels for panel (b). Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 5 shows heterogeneous elasticities by commodity–continent pair. In Africa, elasticities are large and positive for tree and perennial crops, including cocoa (0.38), coffee (0.22), fibre crops (0.18), nuts (0.26), other oilseeds (0.13), palm (0.11), rubber (0.10), pulses/legumes (0.15), and stimulants/spices/aromatic crops (0.16), while staples such as cassava, rice, maize, fruits, vegetables, and soybeans have coefficients statistically non-significant. Sugar crops are negative (−0.17). Southeast Asia also exhibits strong positive responses for land-extensive export crops: palm (0.33), rubber (0.25), cocoa (0.27), and stimulants/spices/aromatics (0.31). Rice (0.09) and other oilseeds (0.11) have also positive and significant estimates but smaller in magnitude. By contrast, cassava (−0.21), other cereals (−0.17), and soybeans (−0.12) shows negative elasticities, which could be becuase of limited forest-expansion margins available for these staples or a shift of their production onto already cleared land.

In South America, pasture/cattle (0.21) and soybeans (0.23) have the largest positive elasticities, followed by cocoa (0.26), coffee (0.18), and sugar crops (0.13), aligning with the well-documented literature of larger deforestation footprint shown by cattle, soy and associated perennial crops. Most other crops (fruits, maize, nuts, other cereals, other oilseeds, palm, pulses, rice, rubber, vegetables) have non-significant coefficients. North and Central America show positive elasticities for several export-oriented crops, including coffee (0.26), fibre crops (0.20), palm (0.18), nuts (0.16), pulses/legumes (0.14), and, more modestly, pasture/cattle (0.11). Cassava (−0.44) and rice (−0.13) are significantly negative.

In the Rest of Asia, cassava (−0.86) and palm (−0.58) have large negative elasticities, and maize is modestly negative (−0.07), whereas fibre crops (0.22), pulses/legumes (0.19), other oilseeds (0.15), nuts (0.14), pasture/cattle (0.12), and stimulants/spices/aromatics (0.27) show sizeable positive responses. This mix suggests that foreign demand in this region is more tightly linked to deforestation for specific cash and perennial crops, while some staple crops may expand on already cleared land or shift away from forest frontiers. North Asia is dominated by negative elasticities for cassava (−0.76), palm (−0.75), rice (−0.28), pulses/legumes (−0.18), sugar crops (−0.18), fruits (−0.16), and several other crops, with rubber (0.22) as the only clear positive case, indicating limited remaining scope for forest conversion in response to foreign demand for most commodities in this region.

In Europe, most commodity-specific elasticities are small, but there are modest positives for nuts (0.16), other oilseeds (0.16), and other cereals (0.10), and a negative elasticity for rice (−0.15). Oceania shows moderate positives for cocoa (0.32), coffee (0.18), and palm (0.21), and significant negatives for cassava (−0.44), maize (−0.24), and soybeans (−0.36), with other commodities non-significant. In, positive and statistically significant foreign-demand elasticities are concentrated in land-extensive crops such as palm, rubber, cocoa, coffee, fibre crops, soybeans (in some regions), cattle, and selected oilseeds in classic tropical forest frontiers in South America, Southeast Asia, parts of Africa, and the Rest of Asia. In contrast, staple crops (cassava, rice, maize) and many fruits and vegetables often show weak, zero, or even negative effects, consistent with expansion on non-forest land or stronger land-use constraints.These findings mirror commodity-specific evidence from Brazil and other tropical forest frontiers (Meyfroidt et al. 2010; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019; Oliveira et al. 2025; Carreira et al. 2024; Du et al. 2024), and they highlight a relatively small set of high-risk commodity–region combinations that account for the bulk of demand-driven deforestation.



Vegetables 0.02 (0.06) -0.05 (0.06) -0.03 (0.07) -0.10 (0.09) -0.11 (0.10) 0.06 (0.05) -0.06 (0.08) 0.01 (0.05)
Sugar -0.17** (0.08) -0.04 (0.06) 0.07 (0.07) -0.18*** (0.07) -0.14 (0.09) 0.01 (0.05) 0.13** (0.06) 0.04 (0.05)
Stimulants 0.16** (0.07) -0.01 (0.08) 0.09 (0.08) 0.07 (0.10) -0.03 (0.11) 0.27*** (0.09) 0.07 (0.07) 0.31*** (0.08)
Soybeans -0.08 (0.10) 0.01 (0.07) 0.08 (0.06) -0.12 (0.08) -0.36*** (0.07) 0.04 (0.05) 0.23*** (0.06) -0.12* (0.06)
Rubber 0.10* (0.06) 0.13 (0.08) 0.22* (0.12) -0.06 (0.06) 0.06 (0.11) -0.10 (0.14) 0.25*** (0.04)
Rice -0.02 (0.03) -0.15* (0.09) -0.13* (0.08) -0.28*** (0.10) -1.02 (1.28) 0.03 (0.05) -0.08 (0.05) 0.09*** (0.03)
Pulses 0.15*** (0.05) 0.08 (0.05) 0.14*** (0.04) -0.18** (0.08) -0.07 (0.08) 0.19*** (0.04) 0.02 (0.06) 0.01 (0.11)
Palm 0.11** (0.05) 0.18*** (0.06) -0.75*** (0.09) 0.21*** (0.05) -0.58*** (0.12) 0.07 (0.09) 0.33*** (0.04)
Other Oilseeds 0.13*** (0.03) 0.16*** (0.04) 0.09 (0.06) -0.02 (0.08) 0.07 (0.05) 0.15*** (0.04) 0.06 (0.08) 0.11** (0.05)
Other Cereals -0.11 (0.08) 0.10* (0.05) 0.02 (0.06) -0.12 (0.08) -0.05 (0.10) 0.05 (0.06) 0.02 (0.06) -0.17** (0.08)
Nuts 0.26*** (0.04) 0.16** (0.06) 0.16** (0.06) -0.12 (0.09) -0.05 (0.09) 0.14** (0.06) -0.07 (0.09) 0.10 (0.06)
Maize 0.03 (0.04) 0.02 (0.05) 0.03 (0.05) -0.08 (0.05) -0.24* (0.14) -0.07* (0.04) 0.01 (0.05) -0.02 (0.05)
Fruits 0.03 (0.04) -0.06 (0.05) 0.04 (0.06) -0.16* (0.09) -0.06 (0.06) -0.01 (0.04) -0.01 (0.05) 0.02 (0.03)
Fibre 0.18*** (0.03) 0.07 (0.07) 0.20*** (0.05) -0.02 (0.07) 0.06 (0.05) 0.22*** (0.04) 0.04 (0.08) -0.09 (0.06)
Coffee 0.22*** (0.07) 0.26*** (0.09) -0.20* (0.10) 0.18** (0.08) 0.02 (0.10) 0.18** (0.09) 0.17* (0.10)
Cocoa 0.38*** (0.11) 0.13 (0.12) 0.32*** (0.10) 0.00 (0.15) 0.26** (0.13) 0.27*** (0.10)
Cattle 0.08** (0.03) 0.07 (0.04) 0.11** (0.05) -0.01 (0.06) -0.05 (0.06) 0.12*** (0.04) 0.21*** (0.03) -0.05 (0.03)
Cassava 0.03 (0.05) -0.44** (0.21) -0.76*** (0.10) -0.44** (0.21) -0.86*** (0.12) -0.15* (0.09) -0.21** (0.09)
Africa
Europe
North and Central America
North Asia
Oceania
Rest of Asia
South America
Southeast Asia
Coefficient Estimate
0.0
-0.5
-1.0

Figure 5: Deforestation elasticities of commodities with respect to foreign demand for each continent. The estimates are based on PPML estimation. The fixed effects include country–year and commodity–year fixed effects. The standard errors are clustered at country-commodity and year levels. Red color indicates positive elasticities and green indicates negative elasticities. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.2 Effects of export sales on deforestation

We estimate the effect of export sales on deforestation using a control-function PPML estimator, instrumenting export sales with two instruments: FD and $\widehat{FD}$. We present (i) pooled effects, (ii) heterogeneous effect by commodity group, (iii) heterogeneous effect by continent, and (iv) heterogeneous effect by continent-commodity pairs. The specification details are in appendix 12.

Table 3 reports pooled estimates of the elasticity of deforestation with respect to export sales, instrumented with FD in column (1) and with $\widehat{FD}$ in column (2). Using FD, the export elasticity is 0.382, while using $\widehat{FD}$ it is 0.244. These estimates suggest that a 10% increase in export sales leads to 2.4 to 3.8% increase in deforestation associated with these commodities. The control-function residual is small and imprecise when FD is used as the instrument, but positive significant when we use $\widehat{FD}$, indicating that exports are endogenous and that the CF term is absorbing remaining correlation between exports and unobservables. Further, estimates using $\widehat{FD}$ are systematically smaller than those using FD. The former measure removes exporter-specific and bilateral shocks that move both export shares and deforestation (for example, domestic policies or bilateral infrastructure investments), isolating variation in destination–product demand and "inward resistance" common to all origins. The attenuation of elasticities under $\widehat{FD}$ is therefore consistent with $\widehat{FD}$ providing a more conservative, but arguably cleaner, measure of exogeneity.

Table 3: Effect of export sales on deforestation

	(1)	(2)
Log(Exports)	0.382***	0.244
	(0.078)	(0.116)
	[0.175, 0.467]	[-0.058, 0.397]
Residual	0.056	0.177**

	(1)	(2)
	(0.080)	(0.097)
	[-0.076, 0.219]	[0.020, 0.398]
Observations	41,103	41,103
Pseudo R-squared	0.855	0.855
Country × Year FE	Yes	Yes
Commodity × Year FE	Yes	Yes
Instrument	FD	$\widehat{FD}$

Notes: The control-function residual is from the first-stage regression. Bootstrap standard errors based on 1000 replications are reported in parenthesis. 95% bootstrap percentile CIs in brackets. Column (1) instruments with FD and column (2) instruments with $\widehat{FD}$* p < 0.10, ** p < 0.05, *** p < 0.01 (based on bootstrap percentile CIs)

Figure 6 illustrates the heterogeneous effects of export sales on deforestation by commodities and continents. The results shows that the export sales effects are largest for land-intensive perennial tree crops, such as stimulants (0.69 to 0.81), rubber (0.62 to 0.75), palm (0.61 to 0.73), cocoa (0.55 to 0.67) and nuts (0.48 to 0.60). Several mechanisms can rationalize these patterns. First, establishing plantations for these crops involves high fixed costs of clearing and planting, while the marginal cost of expanding onto cheap frontier land is low. By contrast, intensifying production on existing orchards is capital-intensive and constrained by agronomic limits such as tree spacing and intercropping options. Export demand shocks are therefore more likely to be accommodated through horizontal expansion into forests than through yield gains, generating large deforestation elasticities (Goldman et al. 2020). Second, these are high-value, export-oriented commodities, and high-value tree crops have been shown to exhibit stronger land-use responses to trade shocks than lower-value staples (Jadin, Meyfroidt and Lambin 2016).

Other important commodity groups with sizeable elasticities include soybeans (0.37–0.50), other cereals (0.37–0.50), cattle (0.30–0.44), sugar crops (0.27–0.39), and coffee (0.26–0.38). In contrast, staple and horticultural crops tend to have small and statistically insignificant elasticities: cassava (−0.16), rice (0.01), maize (0.01), pulses (0.09), fruits (0.07), vegetables (0.08), and other oilseeds (0.15). These sectors can more readily expand on already cleared land or via input-driven intensification, so additional export sales need not translate into new forest conversion. Interestingly, effects of some commodities, such as stimulants and other cereals, and continent, Europe, responses with larger deforestation for export sales and weaker for foreign demand. Interestingly, some commodities (such as stimulants and other cereals) and Europe as a region show much larger effects for export sales than for foreign demand. For Europe, the elasticity is relatively high (0.358–0.50), whereas the foreign-demand effect is close to zero (0.03). This pattern suggests that deforestation in Europe is driven more by factors other than external demand. When foreign demand increases, European producers can often respond by intensifying production on existing land or by switching land from other crops rather than expanding into forests, so average deforestation does not move much. By contrast, the export-sales coefficient captures what happens in those episodes where exports from Europe actually expand. In those cases, when additional exports do come from land expansion, the associated increase in deforestation is large, even if such episodes are relatively rare in the aggregate. However, continents—notably the Rest of Asia, North Asia, Oceania, and Africa—show the statistically insignificant elasticities, that is due to different elasticities measures of commodities inside these continents.

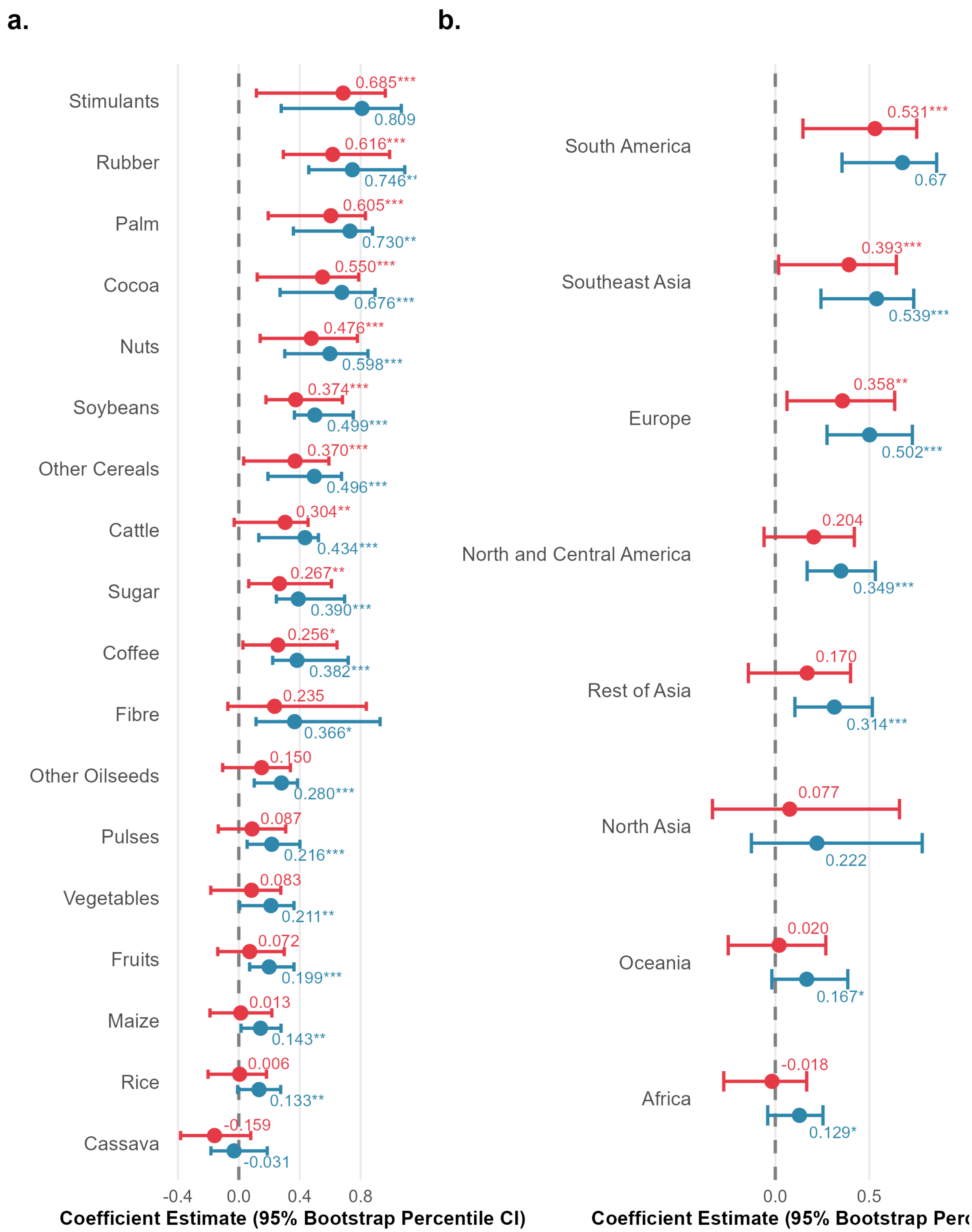


Figure 6: Heterogeneous deforestation elasticities with respect to exports. Panel (a) shows esti-

mates by commodity; Panel (b) shows estimates by continent. Red error bars correspond to estimates instrumented with $\widehat{FD}$ while blue error bars correspond to estimates instrumented with FD. All specifications include country-year and commodity-year fixed effect and are estimated by control-function PPML. The bootstrap standard errors of 1000 replications are reported in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 7 disaggregates the export–deforestation elasticities by continent–commodity pair. Export-driven deforestation is again concentrated in humid-tropical frontiers in South America, Southeast Asia, and Africa, where suitable agro-climatic conditions for palm oil, cocoa, rubber, coffee, nuts, and stimulants overlap strongly with remaining forests. In South America, almost all export commodities exhibit large positive elasticities. Cocoa (0.82), coffee (0.71), palm (0.76), soybeans (0.64), rubber (0.64), nuts (0.70), stimulants/spices/aromatic crops (0.71), sugar crops (0.49), pasture/cattle (0.52), fibre crops (0.53), other cereals (0.54), other oilseeds (0.43), pulses/legumes (0.41), maize (0.32), fruits (0.32), vegetables (0.31), and rice (0.29) show statistically significant responses. In Southeast Asia, export elasticities are also large for land-extensive tree crops: palm (0.51), coffee (0.46), rubber (0.38), nuts (0.54), and stimulants/spices/aromatic crops (0.57) are strongly positive; cocoa (0.51), soybeans (0.28), and sugar crops (0.22) are positive but somewhat less precisely estimated. By contrast, coefficients for cassava, rice, maize, and other cereals are not statistically different from zero.

In Africa, tree and perennial crops again dominate the response. Cocoa (0.57), coffee (0.58), palm (0.42), nuts (0.69), stimulants/spices/aromatics (0.49), fibre crops (0.38), and soybeans (0.35) have positive and significant elasticities, while staples such as cassava, maize, rice, fruits, vegetables, and sugar crops have insignificant coefficients. In the Rest of Asia, cassava has a large negative elasticity (−0.62), whereas nuts (0.57), stimulants/spices/aromatics (0.50), fibre crops (0.44), soybeans (0.36), and, more weakly, other oilseeds (0.21) show positive responses. In Europe, export elasticities are positive and often large across a wide range of crops: nuts (0.89), soybeans (0.61), fibre crops (0.59), stimulants/spices/aromatics (0.59), other cereals (0.52), other oilseeds (0.47), pulses/legumes (0.46), sugar crops (0.37), pasture/cattle (0.37), maize (0.33), fruits (0.25), and vegetables (0.26) show positive and significant elasticities, while rice is positive but imprecisely estimated (0.18).

Results are mixed in other regions. In North and Central America, several export-oriented commodities are positive, which are coffee (0.68), cocoa (0.52), nuts (0.67), palm (0.58), soybeans (0.49), stimulants/spices/aromatics (0.56), pulses/legumes (0.33), fibre crops (0.56), sugar crops (0.31), and pasture/cattle (0.26). Maize and rice have smaller and insignificant coefficients. Oceania shows moderate positives for cocoa (0.65), coffee (0.55), nuts (0.63), stimulants/spices/aromatics (0.45), fibre crops (0.45), and other oilseeds (0.35), while most staple crops are again insignificant; rice stands out with a negative elasticity (−0.26). North Asia is generally muted, with coefficients for all commodities statistically insignificant.

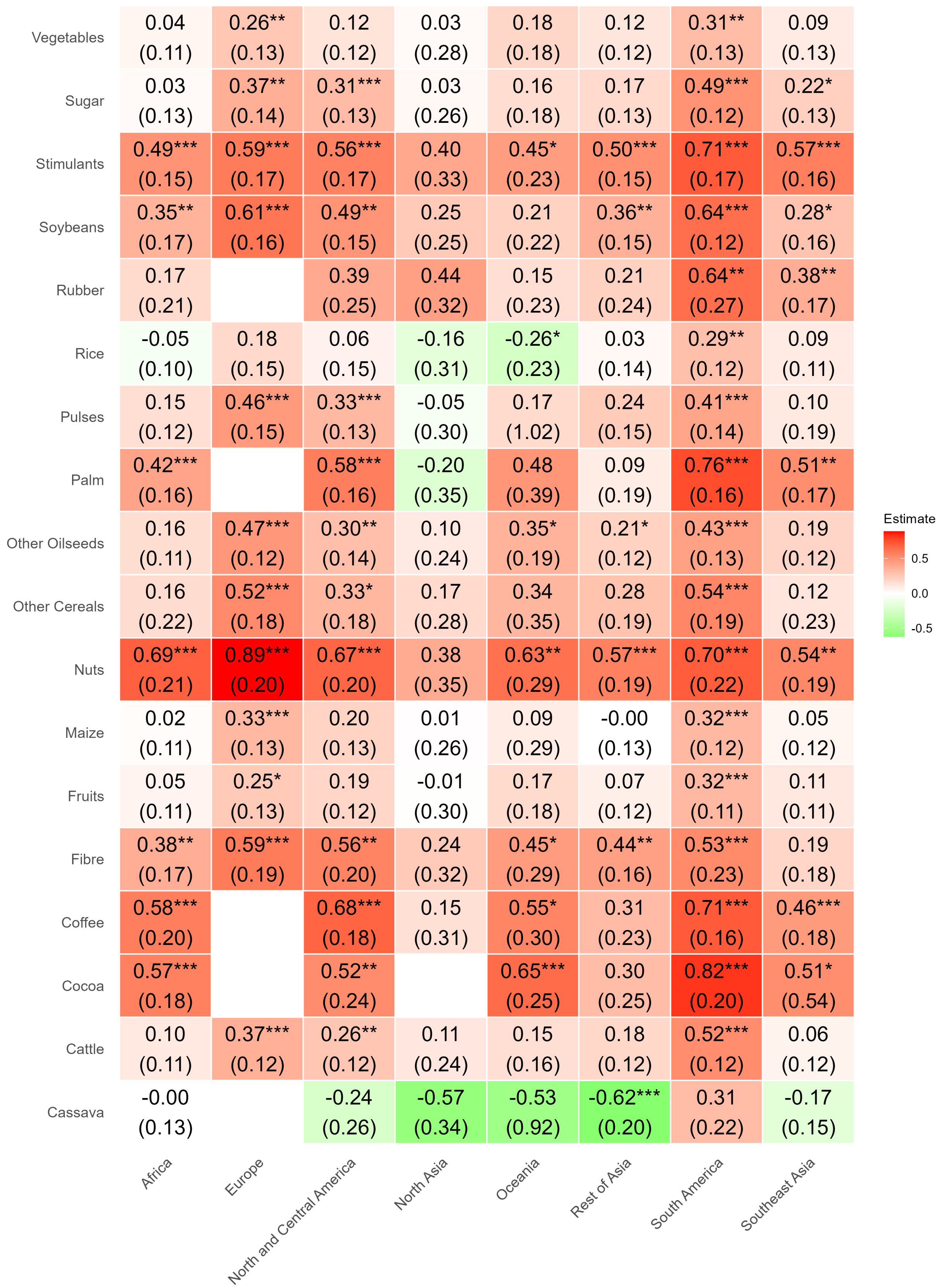

Vegetables
0.04 (0.11)
0.26** (0.13)
0.12 (0.12)
0.03 (0.28)
0.18 (0.18)
0.12 (0.12)
0.31** (0.13)
0.09 (0.13)
Sugar
0.03 (0.13)
0.37** (0.14)
0.31*** (0.13)
0.03 (0.26)
0.16 (0.18)
0.17 (0.13)
0.49*** (0.12)
0.22* (0.13)
Stimulants
0.49*** (0.15)
0.59*** (0.17)
0.56*** (0.17)
0.40 (0.33)
0.45* (0.23)
0.50*** (0.15)
0.71*** (0.17)
0.57*** (0.16)
Soybeans
0.35** (0.17)
0.61*** (0.16)
0.49** (0.15)
0.25 (0.25)
0.21 (0.22)
0.36** (0.15)
0.64*** (0.12)
0.28* (0.16)
Rubber
0.17 (0.21)
0.39 (0.25)
0.44 (0.32)
0.15 (0.23)
0.21 (0.24)
0.64** (0.27)
0.38** (0.17)
Rice
-0.05 (0.10)
0.18 (0.15)
0.06 (0.15)
-0.16 (0.31)
-0.26* (0.23)
0.03 (0.14)
0.29** (0.12)
0.09 (0.11)
Pulses
0.15 (0.12)
0.46*** (0.15)
0.33*** (0.13)
-0.05 (0.30)
0.17 (1.02)
0.24 (0.15)
0.41*** (0.14)
0.10 (0.19)
Palm
0.42*** (0.16)
0.58*** (0.16)
-0.20 (0.35)
0.48 (0.39)
0.09 (0.19)
0.76*** (0.16)
0.51** (0.17)
Other Oilseeds
0.16 (0.11)
0.47*** (0.12)
0.30** (0.14)
0.10 (0.24)
0.35* (0.19)
0.21* (0.12)
0.43*** (0.13)
0.19 (0.12)
Other Cereals
0.16 (0.22)
0.52*** (0.18)
0.33* (0.18)
0.17 (0.28)
0.34 (0.35)
0.28 (0.19)
0.54*** (0.19)
0.12 (0.23)
Nuts
0.69*** (0.21)
0.89*** (0.20)
0.67*** (0.20)
0.38 (0.35)
0.63** (0.29)
0.57*** (0.19)
0.70*** (0.22)
0.54** (0.19)
Maize
0.02 (0.11)
0.33*** (0.13)
0.20 (0.13)
0.01 (0.26)
0.09 (0.29)
-0.00 (0.13)
0.32*** (0.12)
0.05 (0.12)
Fruits
0.05 (0.11)
0.25* (0.13)
0.19 (0.12)
-0.01 (0.30)
0.17 (0.18)
0.07 (0.12)
0.32*** (0.11)
0.11 (0.11)
Fibre
0.38** (0.17)
0.59*** (0.19)
0.56** (0.20)
0.24 (0.32)
0.45* (0.29)
0.44** (0.16)
0.53*** (0.23)
0.19 (0.18)
Coffee
0.58*** (0.20)
0.68*** (0.18)
0.15 (0.31)
0.55* (0.30)
0.31 (0.23)
0.71*** (0.16)
0.46*** (0.18)
Cocoa
0.57*** (0.18)
0.52** (0.24)
0.65*** (0.25)
0.30 (0.25)
0.82*** (0.20)
0.51* (0.54)
Cattle
0.10 (0.11)
0.37*** (0.12)
0.26** (0.12)
0.11 (0.24)
0.15 (0.16)
0.18 (0.12)
0.52*** (0.12)
0.06 (0.12)
Cassava
-0.00 (0.13)
-0.24 (0.26)
-0.57 (0.34)
-0.53 (0.92)
-0.62*** (0.20)
0.31 (0.22)
-0.17 (0.15)
Africa
Europe
North and Central America
North Asia
Oceania
Rest of Asia
South America
Southeast Asia
Estimate
0.5
0.0
-0.5

Figure 7: Deforestation elasticities of commodities with respect to exports for each continent. The estimates are based on control-function PPML estimation. The fixed effects include country–year and commodity–year fixed effects. Bootstrap standard errors based on 1,000 replications are reported in parenthesis. Red color indicates positive elasticities and green indicates negative elasticities. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.3 Robustness checks

To assess robustness to functional form, we estimate the effect of international demand using four alternative outcome transformations, which are log(Deforestation), log(1+Deforestation), asinh(Deforestation) and level. Across these specifications, we maintain the same fixed effects and clustering, however to measure the effect of export demand we use two stage least squares (2-SLS) estimator. Qualitatively, the results are similar across all outcomes (see appendix 13). Signs and statistical significance are preserved in the pooled sample, and the pattern of heterogeneous responses by commodity (stronger for land-intensive frontier commodities such as cocoa, palm, rubber, soybeans, and pasture) and by region (larger in South America and Southeast Asia) remains. Magnitudes adjust as expected with the transformation. PPML tends to give greater weight to observations with larger conditional means. Log-based models emphasize proportional changes among positive observations. Inverse hyperbolic sign sits between these two. In all cases, instrumented specifications continue to show a positive and statistically significant effects of export effect.

The consistency of the estimates from our shift-share design relies on the exogeneity of demand at product-destination-year, (s, j, t), for each country-commodity-year, (i, k, t). We treat the shares as fixed and sufficiently small that they do not drive our estimates. To test that our results are not driven by the shares themselves, we randomly shuffle s^k_{ist} across country-commodity pairs 1000 times and re-estimate the effect of foreign demand on deforestation. This is equivalent to drawing 1000 datasets and re-estimating β. Figure 8 presents the distribution of the estimated coefficients and the associated t-statistics from this exercise, together with their 95% confidence intervals. We find that β and t-statistics estimated from the original data are statistically non-significant from those obtained under the permulations of the shares. The confidence interval of t-statistics also suggests that most coefficients are statistically significant. Our results indicates that the effect are not significantly driven by shares.

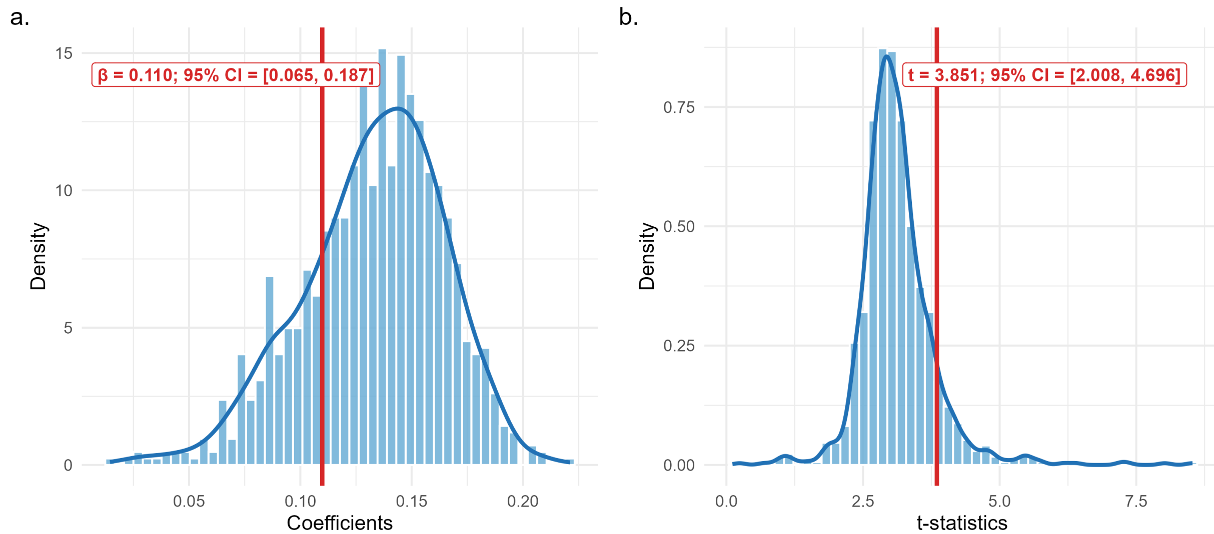


Figure 8: Distributions of estimated coefficients and t-statistics from permutation samples. Note: The density plots are based on 1,000 iterations. The 95% confidence intervals are constructed using percentile confidence intervals at the 2.5th and 97.5th percentiles of the bootstrap distribution. The values 0.110 and 3.851 are the coefficient estimate and t-statistic from the actual data, respectively. The red vertical solid lines represent the coefficient and t-statistic estimated from the actual data.

4.4 Discussion and conclusion

International trade has long been identified as a central driver of agricultural expansion and deforestation in the tropics (e.g., Meyfroidt et al. 2010; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019; Godar and Gardner 2019). Recent policy initiatives—from private zero-deforestation commitments to new regulatory frameworks such as the EU Deforestation Regulation and the UK Environmental Improvement Plan—increasingly rely on trade-linked measures to curb forest loss (e.g., Lambin et al. 2018; Garrett et al. 2019). Our study speaks directly to this agenda by quantifying how international demand, captured through foreign demand and export sales, relates to deforestation across 18 commodity groups and multiple (sub-)continents between 2001 and 2022.

Conceptually, we map international demand into deforestation through three channels: (i) from international prices to export sales to deforestation, (ii) directly from foreign demand to export sales (for instance via forward contracting, financing, or investment in processing capacity) to deforestation, and (iii) directly from international prices to land outcomes through domestic price pass-through, speculative behavior, and enforcement responses. Empirically, our specifications focus on the export-mediated channel. Commodity-year fixed effects absorb common global price shocks, while country-year fixed effects soak up domestic supply, macroeconomic conditions, and broad policy changes. We construct a shift–share foreign-demand measure that aggregates destination-specific product demand for each country–commodity pair, and then estimate (i) reduced-form Poisson models relating foreign demand directly to deforestation and (ii) control-function PPML specifications that use foreign demand as an instrument for export sales.

Across pooled specifications, higher foreign demand is positively associated with deforestation, and instrumented exports have a positive and statistically significant effect across several outcome transformations. Our preferred elasticities imply that a 10% increase in international demand or export sales leads to roughly a 2–4% increase in deforestation attributed to the corresponding commodities. These magnitudes are broadly consistent with recent causal estimates for Brazil (e.g., Du et al. 2024; Carreira et al. 2024) and with global evidence that a substantial share of deforestation emissions is embodied in agricultural trade (Meyfroidt et al. 2010; Pendrill, Persson, Godar, Kastner, Moran, et al. 2019). Because commodity-year fixed effects absorb international shocks and country-year fixed effects absorb domestic governance and policy shocks, these elasticities should be interpreted primarily as export-mediated rather than pure price effects. Allowing responses to vary by commodity and continents reveals pronounced heterogeneity that sheds light on the mechanisms behind trade-induced forest loss. Export-deforestation elasticities are consistently largest for land-intensive perennial tree crops, such as stimulants and spices, rubber, palm oil, cocoa, nuts, coffee, sugar crops, including soybeans and cattle. We suggest three potential explanations why these commodities exhibit such strong responses to international demand.

First, these crops are land-intensive perennial systems with high fixed costs of establishment but relatively low marginal costs of expansion on frontier land. Establishing oil-palm, cocoa, rubber, coffee, or nut plantations requires large, up-front investments in clearing, planting, and sometimes basic infrastructure. Once planted, trees are costly to re-space and production is locked into a given location for decades. Intensifying production on existing plots is therefore limited by agronomic constraints (tree spacing, shading, intercropping possibilities) and requires substantial capital. By contrast, expanding onto nearby forest land becomes relatively cheap once roads and processing facilities are in place. Export demand shocks are thus more likely to be accommodated by horizontal expansion into forests than by yield gains, generating high deforestation elasticities for these crops (Goldman et al. 2020; Renier et al. 2025).

Second, these commodities are high-value, export-oriented crops. Their high gross margins make it profitable for firms and smallholders to bear the fixed costs of frontier expansion when international demand rises, especially where land is cheap and tenure or enforcement is weak. The literature on Cambodia and Ghana shows that even shocks to staple prices can redirect land toward higher-value export crops when households seek to hedge income risk (Wilcox et al. 2025; Krah 2021; Lundberg and Abman 2021). Our findings generalize this logic: high-value export crops and cattle exhibit much stronger land-use responses to demand shocks than staples and many horticultural crops, which can often expand on already cleared land or through input-driven intensification.

Third, the production of these crops is agro-climatically concentrated in humid tropical regions where accessible forest margins remain abundant. Suitable climate and soils for palm oil, cocoa, rubber, coffee, and many nut and stimulant crops strongly overlap with forested frontier areas in Southeast Asia, West and Central Africa, and South America (Berman et al. 2021; Goldman et al. 2020). In these landscapes, the main adjustable land margin is forest, whereas scope for reallocating production to degraded or marginal lands is more limited than for temperate or semi-arid crops. The continent–commodity estimates confirm this spatial mechanism: the largest elasticities arise in South America and Southeast Asia, followed by parts of Africa, precisely where high-value perennial crops and extensive cattle systems intersect with remaining tropical forests.

Taken together, these mechanisms align our findings with, and extend, existing evidence from more narrowly defined settings. For Brazil, a large literature has emphasized the role of soy and cattle prices in driving deforestation, the moderating role of environmental regulation, and the importance of indirect land-use change (e.g., Harding et al. 2021; Assunção et al. 2015; Bragança 2018; Arima et al. 2011; Hargrave and Kis-Katos 2013). For Cambodia and Ghana, recent work highlights how staple price levels and volatility interact with cash crops and cocoa expansion to shape forest outcomes (Wilcox et al. 2025; Krah 2021; Lundberg and Abman 2021; Renier et al. 2025). Our contribution is to provide a unified, multi-commodity, multi-region perspective using a common identification strategy, showing that a relatively small set of humid-tropical export frontiers—palm, soy, beef, cocoa, coffee, rubber, and related tree crops in South America, Southeast Asia, and parts of Africa—account for a disproportionate share of trade-induced forest loss.

Several limitations should temper the interpretation of our estimates. First, commodity-attributed deforestation and the mapping from HS trade codes to aggregated commodity groups are subject to measurement error, particularly for multi-use crops and mixed production systems. This likely attenuates some elasticities and may blur differences among closely related commodities. Second, by construction, our fixed-effects structure absorbs common global price movements and macro shocks. We therefore do not separately identify the pure price-only channel emphasized in work that explicitly models price pass-through and technology responses (e.g., Berman et al. 2021; Carreira et al. 2024). Third, anticipatory behavior and multi-year adjustments—such as investments in processing capacity, transport infrastructure, or land speculation—may generate lagged or non-linear responses that we only partially capture with our panel structure. Finally, although country-year fixed effects control for broad governance and institutional changes, crop- and region-specific policies (for example, commodity-specific moratoria, concession rules, or credit programs) may still bias estimates.

Despite these caveats, our results have important policy implications. Our elasticities can be used as behavioral parameters to link trade models with spatially explicit deforestation outcomes. They are directly applicable for ex-ante evaluations of trade-linked environmental regulations, such as the EU Deforestation Regulation, including their potential for leakage across crops, regions, and supply chains in a telecoupled land-use system (Meyfroidt et al. 2010; Godar and Gardner 2019). Further, our estimates provides information on commodities and regions where the pass-through from international demand to land conversion is strongest. This is directly helpful for designing of anti-deforestation efforts. Future work could build on our approach by moving to finer spatial scales (sub-national or landscape-level), integrating explicit measures of agro-climatic suitability, and modeling indirect land-use change between commodities and regions, as in recent studies of soy, cattle, and cocoa (e.g., Arima et al. 2011; Renier et al. 2025). Another promising avenue is to combine our export-demand framework with detailed data on land rights and tenure system to quantify how governance interacts with international demand in shaping forest cover.

References

Abman, R., and C. Lundberg. 2020. "Does free trade increase deforestation? The effects of regional trade agreements." *Journal of the Association of Environmental and Resource Economists* 7(1):35–72.

Ajanaku, B., and A. Collins. 2021. "Economic growth and deforestation in african countries: Is the environmental kuznets curve hypothesis applicable?" *Forest Policy and Economics* 129:102488.

Alroy, J. 2017. "Effects of habitat disturbance on tropical forest biodiversity." *Proceedings of the National Academy of Sciences* 114(23):6056–6061.

Arima, E., P. Richards, R. Walker, and M. Caldas. 2011. "Statistical confirmation of indirect land use change in the brazilian amazon." *Environmental Research Letters* 6:024010.

Arisco, N.J., C. Peterka, C. Diniz, B. Singer, and M.C. Castro. 2024. "Ecological change increases malaria risk in the brazilian amazon." *Proceedings of the National Academy of Sciences of the United States of America* 121.

Assunção, J., C. Gandour, and R. Rocha. 2015. "Deforestation slowdown in the brazilian amazon: Prices or policies?" *Environment and Development Economics* 20:697–722.

Balboni, C., A. Berman, R. Burgess, and B.A. Olken. 2022. "The economics of tropical deforestation." Available at: https://economics.mit.edu/sites/default/files/2022-09/ARE_Tropical_Deforestation-3.pdf.

Barbier, E.B. 2004. "Explaining agricultural land expansion and deforestation in developing countries." *American Journal of Agricultural Economics* 86(5):1347–1353.

Beckman, J., R.D. Sands, A.A. Riddle, T. Lee, and J.M. Walloga. 2017. "International trade and deforestation: Potential policy effects via a global economic model." No. ERR-229, U.S. Department of Agriculture, Economic Research Service. Available at: https://ers.usda.gov/sites/default/files/_laserfiche/publications/83299/ERR-229.pdf?v=66067.

Bellemare, M.F., and C.J. Wichman. 2020. "Elasticities and the inverse hyperbolic sine transformation." *Oxford Bulletin of Economics and Statistics* 82(1):50–61.

Benhin, J.K. 2006. "Agriculture and deforestation in the tropics: A critical theoretical and empirical review." *AMBIO: A Journal of the Human Environment* 35(1):9–16.

Berazneva, J., and T.S. Byker. 2017. "Does forest loss increase human disease? Evidence from nigeria." *The American economic review* 107 5:516–21.

Berman, N., M. Couttenier, A. Leblois, and R. Soubeyran. 2023. "Crop prices and deforestation in the tropics." *Journal of Environmental Economics and Management* 119:102819.

Berman, N., M. Couttenier, A. Leblois, and R. Soubeyran. 2021. "Crop prices and deforestation in the tropics." *Journal of Environmental Economics and Management*.

Borusyak, K., P. Hull, and X. Jaravel. 2024. "A practical guide to shift-share instruments." NBER working paper series No. 33236, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w33236.

Borusyak, K., P. Hull, and X. Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of Economic Studies* 89(1):181–213.

Bragança, A. 2018. "The effects of crop-to-beef relative prices on deforestation: Evidence from the tapajós basin." *Environment and Development Economics* 23:391–412.

Burgess, R., F. Costa, and B.A. Olken. 2019. "The brazilian amazon's double reversal of fortune." Available at: https://www.lse.ac.uk/economics/Assets/Documents/personal-pages/robin-burgess/the-brazilian-amazons-double-reversal-of-fortune-manuscript.pdf.

Burgess, R., M. Hansen, B.A. Olken, P. Potapov, and S. Sieber. 2012. "The political economy of deforestation in the tropics." *The Quarterly Journal of Economics* 127(4):1707–1754. Available at: https://doi.org/10.1093/qje/qjs034.

Caravaggio, N. 2020. "A global empirical re-assessment of the environmental kuznets curve for deforestation." *Forest Policy and Economics* 119:102282.

Carreira, I., F. Costa, and J.P. Pessoa. 2024. "The deforestation effects of trade and agricultural productivity in brazil." *Journal of development economics* 167:103217.

Chaves, L.S.M., J. Fry, A. Malik, A. Geschke, M.A.M. Sallum, and M. Lenzen. 2020. "Global consumption and international trade in deforestation-associated commodities could influence malaria risk." *Nature Communications* 11:1258. Available at: https://www.nature.com/articles/s41467-020-15023-2.

Cisneros, E., K. Kis-Katos, and N. Nuryartono. 2021. "Palm oil and the politics of deforestation in indonesia." *Journal of Environmental Economics and Management* 108:102453. Available at: https://doi.org/10.1016/j.jeem.2021.102453.

Crepin, L., and C. Nedoncelle. 2023. "Foreign demand, soy exports, and deforestation." Available at: http://repec.org/frsug2024/France24_Crepin.pdf.

Culas, R.J. 2007. "Deforestation and the environmental kuznets curve: An institutional perspective." *Ecological Economics* 61(2-3):429–437. Available at: https://doi.org/10.1016/j.ecolecon.2006.03.014.

Damm, Y., J. Börner, N. Gerber, and B. Soares-Filho. 2024. "Health benefits of reduced deforestation in the brazilian amazon." *Communications Earth & Environment* 5:693. Available at: https://www.nature.com/articles/s43247-024-01840-7.

Du, X., L. Li, and E. Zou. 2024. "Trade, trees, and lives." No. 33143, National Bureau of Economic Research. Available at: https://www.nber.org/system/files/working_papers/w33143/w33143.pdf.

European Parliament and of the Council. 2023. "Regulation (EU) 2023/1115 of the european parliament and of the council of 31 may 2023 on the making available on the union market and the export from the union of certain commodities and products associated with deforestation and forest degradation and repealing regulation (EU) no 995/2010 (text with EEA relevance)." *Official Journal of the European Union* 66:150–206. Available at: https://eur-lex.europa.eu/legal-content/ES/TXT/PDF/?uri=CELEX:32023R1115.

Farrokhi, F., E. Kang, H.S. Pellegrina, and S. Sotelo. 2025. "Deforestation: A global and dynamic perspective." National Bureau of Economic Research. Available at: https://www.nber.org/system/files/working_papers/w34150/w34150.pdf.

Garcia, E.S., A.L.S. Swann, J.C. Villegas, D.D. Breshears, D.J. Law, S.R. Saleska, and S.C. Stark. 2016. "Synergistic ecoclimate teleconnections from forest loss in different regions structure global ecological responses." *PLoS ONE* 11(11):e0165042. Available at: https://doi.org/10.1371/journal.pone.0165042.

Garrett, R., S. Levy, K. Carlson, T. Gardner, J. Godar, J. Clapp, P. Dauvergne, R. Heilmayr, Y. Waroux, B. Ayre, R. Barr, B. Døvre, H. Gibbs, S. Hall, S. Lake, J. Milder, L. Rausch, R. Rivero, X. Rueda, R. Sarsfield, B. Soares-Filho, and N.B. Villoria. 2019. "Criteria for effective zero-deforestation commitments." *Global Environmental Change*.

Gaulier, G., and S. Zignago. 2010. "BACI: International trade database at the product-level (the 1994-2007 version)." *SSRN Electronic Journal*.

Giam, X. 2017. "Global biodiversity loss from tropical deforestation." *Proceedings of the National Academy of Sciences* 114(23):5775–5777.

Godar, J., and T. Gardner. 2019. "Trade and land-use telecouplings." In *Telecoupling: Exploring land-use change in a globalised world*. Springer, pp. 149–175.

Goldman, E., M. Weisse, N. Harris, and M. Schneider. 2020. "Estimating the role of seven commodities in agriculture-linked deforestation: Oil palm, soy, cattle, wood fiber, cocoa, coffee, and rubber." *Technical Note, World Resources Institute* 22.

Harding, T., J. Herzberg, and K. Kuralbayeva. 2021. "Commodity prices and robust environmental regulation: Evidence from deforestation in brazil." *Journal of Environmental Economics and Management*.

Hargrave, J., and K. Kis-Katos. 2013. "Economic causes of deforestation in the brazilian amazon: A panel data analysis for the 2000s." *Environmental and Resource Economics* 54:471–494.

Harstad, B. 2024. "Contingent trade agreements." Available at: https://www.nber.org/system/files/working_papers/w32392/w32392.pdf.

Jadin, I., P. Meyfroidt, and E. Lambin. 2016. "International trade, and land use intensification and spatial reorganization explain costa rica's forest transition." *Environmental Research Letters* 11(3):035005.

Krah, K. 2021. "Export crop price stabilization, land use change, and forest loss: Evidence from ghana." *Unknown Journal*.

Lambin, E., H. Gibbs, R. Heilmayr, K. Carlson, L. Fleck, R. Garrett, Y. le Polain de Waroux, C. McDermott, D. McLaughlin, P. Newton, C. Nolte, P. Pacheco, L. Rausch, C. Streck, T. Thorlakson, and N. Walker. 2018. "The role of supply-chain initiatives in reducing deforestation." *Nature Climate Change* 8:109–116.

Lawrence, D., and K. Vandecar. 2015. "Effects of tropical deforestation on climate and agriculture." *Nature climate change* 5(1):27–36.

Lee, T.-H., and M.-H. Lo. 2021. "The role of el niño in modulating the effects of deforestation in the maritime continent." *Environmental Research Letters* 16(5):054056.

Lundberg, C., and R. Abman. 2021. "Maize price volatility and deforestation." *American Journal of Agricultural Economics*.

Meyfroidt, P., T.K. Rudel, and E.F. Lambin. 2010. "Forest transitions, trade, and the global displacement of land use." *Proceedings of the National Academy of Sciences* 107(49):20917–20922.

Mullahy, J., and E.C. Norton. 2024. "Why transform y? The pitfalls of transformed regressions with a mass at zero." *Oxford Bulletin of Economics and Statistics* 86(2):417–447.

Nedoncelle, C., P. Delacote, and L. Crepin. 2025. "Agricultural exports, market power, and deforestation." Available at: https://hal.inrae.fr/hal-04934081v1/file/markdown_deforestation_feb25.pdf.

Oliveira, G.M. de, Y. Jafari, and J. Börner. 2025. "Heterogeneous effects of export-market preferences on deforestation in brazil." *European Review of Agricultural Economics*:jbaf048.

Papke, L.E., and J.M. Wooldridge. 2008. "Panel data methods for fractional response variables with an application to test pass rates." *Journal of econometrics* 145(1-2):121–133.

Pendrill, F., U.M. Persson, J. Godar, and T. Kastner. 2019. "Deforestation displaced: Trade in forest-risk commodities and the prospects for a global forest transition." *Environmental Re-*

search Letters 14(5):055003.

Pendrill, F., U.M. Persson, J. Godar, T. Kastner, D. Moran, S. Schmidt, and R. Wood. 2019. "Agricultural and forestry trade drives large share of tropical deforestation emissions." *Global Environmental Change* 56:1–10.

Renier, C., T. Addoah, V. Guye, R.D. Garrett, G.V. den Broeck, E.K.H.J. zu Ermgassen, and P. Meyfroidt. 2025. "Direct and indirect deforestation for cocoa in the tropical moist forests of ghana." *Environmental Research: Food Systems*.

Serrão, E.A.O., R.B.L. Cavalcante, P.R. Zanin, R.G. Tedeschi, T.R. Ferreira, and P.R.M. Pontes. 2025. "The effects of teleconnections on water and carbon fluxes in the two south america's largest biomes." *Scientific Reports* 15:1395.

Singh, C., and U.M. Persson. 2024. "DeDuCE: Deforestation and carbon emissions due to agriculture and forestry activities from 2001-2022 (v1.0.1)." Available at: https://doi.org/10.5281/zenodo.13624636.

Snyder, P.K. 2010. "The influence of tropical deforestation on the northern hemisphere climate by atmospheric teleconnections." *Earth Interactions* 14:1–34.

Werth, D., and R. Avissar. 2005. "The local and global effects of southeast asian deforestation." *Geophysical Research Letters* 32(20).

Wilcox, S.W., D.R. Just, and A. Ortiz-Bobea. 2025. "The role of staple food prices in deforestation: Evidence from cambodia." *Land Economics* 101(1):89–118. Available at: https://doi.org/10.3368/le.101.1.100423-0097R.

Wooldridge, J. 2015. "Control function methods in applied econometrics." *The Journal of Human Resources* 50:420–445.

Zu Ermgassen, E.K., J. Godar, M.J. Lathuillière, P. Löfgren, T. Gardner, A. Vasconcelos, and P. Meyfroidt. 2020. "The origin, supply chain, and deforestation risk of brazil's beef exports." *Proceedings of the National Academy of Sciences* 117(50):31770–31779.

Appendix (for online publication)

A1. Selected countries by continent

Continent	Countries
Africa	Angola (AGO), Burundi (BDI), Benin (BEN), Burkina Faso (BFA), Botswana (BWA), Central African Republic (CAF), Côte d'Ivoire (CIV), Cameroon (CMR), Congo - Kinshasa (COD), Congo - Brazzaville (COG), Comoros (COM), Algeria (DZA), Egypt (EGY), Ethiopia (ETH), Gabon (GAB), Ghana (GHA), Guinea (GIN), Gambia (GMB), Guinea-Bissau (GNB), Equatorial Guinea (GNQ), Kenya (KEN), Liberia (LBR), Libya (LBY), Lesotho (LSO), Morocco (MAR), Madagascar (MDG), Mali (MLI), Mozambique (MOZ), Mauritius (MUS), Malawi (MWI), Namibia (NAM), Nigeria (NGA), Rwanda (RWA), Senegal (SEN), Sierra Leone (SLE), Somalia (SOM), Eswatini (SWZ), Chad (TCD), Togo (TGO), Tunisia (TUN), Tanzania (TZA), Uganda (UGA), South Africa (ZAF), Zambia (ZMB), Zimbabwe (ZWE)
Europe	Albania (ALB), Austria (AUT), Belgium (BEL), Bulgaria (BGR), Bosnia & Herzegovina (BIH), Belarus (BLR), Switzerland (CHE), Czechia (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), United Kingdom (GBR), Greece (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Moldova (MDA), North Macedonia (MKD), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Sweden (SWE), Ukraine (UKR)
North Asia	China (CHN), Kazakhstan (KAZ), Mongolia (MNG), Russia (RUS)
North and Central America	Antigua & Barbuda (ATG), Bahamas (BHS), Belize (BLZ), Canada (CAN), Costa Rica (CRI), Cuba (CUB), Dominican Republic (DOM), Guatemala (GTM), Honduras (HND), Haiti (HTI), Jamaica (JAM), St. Kitts & Nevis (KNA), St. Lucia (LCA), Mexico (MEX), Nicaragua (NIC), Panama (PAN), El Salvador (SLV), United States (USA), St. Vincent & Grenadines (VCT)
Oceania	Australia (AUS), Fiji (FJI), New Caledonia (NCL), New Zealand (NZL), Papua New Guinea (PNG), Solomon Islands (SLB), Vanuatu (VUT)

Continent	Countries
Rest of Asia	Afghanistan (AFG), Armenia (ARM), Azerbaijan (AZE), Bangladesh (BGD), Bhutan (BTN), Cyprus (CYP), Georgia (GEO), India (IND), Iran (IRN), Israel (ISR), Japan (JPN), Kyrgyzstan (KGZ), South Korea (KOR), Lebanon (LBN), Sri Lanka (LKA), Nepal (NPL), Pakistan (PAK), North Korea (PRK), Syria (SYR), Tajikistan (TJK), Turkey (TUR), Uzbekistan (UZB)
South America	Argentina (ARG), Bolivia (BOL), Brazil (BRA), Chile (CHL), Colombia (COL), Ecuador (ECU), Grenada (GRD), Guyana (GUY), Peru (PER), Paraguay (PRY), Suriname (SUR), Trinidad & Tobago (TTO), Uruguay (URY), Venezuela (VEN)
Southeast Asia	Brunei (BRN), Indonesia (IDN), Cambodia (KHM), Laos (LAO), Myanmar (Burma) (MMR), Malaysia (MYS), Philippines (PHL), Singapore (SGP), Thailand (THA), Timor-Leste (TLS), Vietnam (VNM)

A2. HS codes aggregation to commodities

Table A2.1: Aggregation of HS codes to commodities

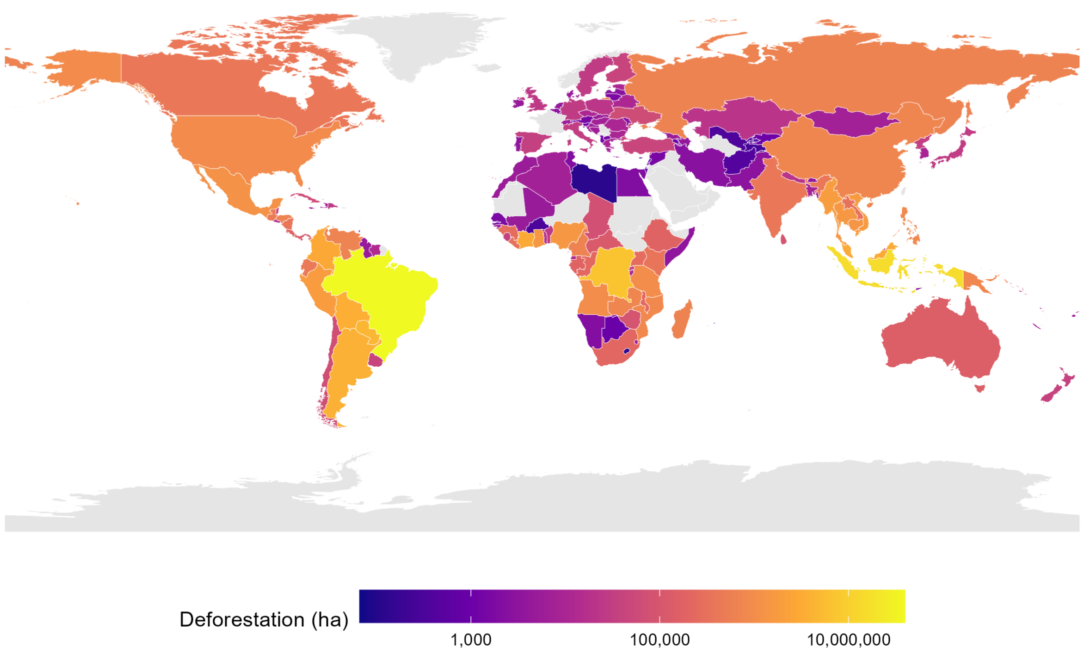
Commodities	HS codes
Cassava	110814, 71410, 110620, 190300
Cattle	50400, 160250, 10290, 150200, 20130, 20230, 160100, 20220, 20610, 20622, 20629, 20621, 10210, 20110, 20120, 21020, 20210, 410190, 410419, 410150, 410120, 410411, 410449, 410712, 410719, 410711, 410441, 410792, 410799, 410791, 10229, 10221, 150290
Cocoa	180690, 180400, 180631, 180610, 180620, 180632, 180310, 180500, 180320, 180100, 180200
Coffee	90190, 90121, 90122, 90111, 210111, 210130, 210112, 90112
Fibre	520100, 240110, 240120, 520210, 520299, 530390, 240130, 140420, 520291, 520300, 530121, 530129, 530110, 530130, 530290, 530310, 530210, 530500
Fruits	80430, 80610, 80620, 220600, 80810, 80450, 81090, 81340, 80711, 81400, 81030, 81330, 200820, 81210, 81290, 200860, 80930, 80520, 200799, 220429, 200990, 80420, 80410, 220421, 80300, 80440, 80510, 220590, 80720, 200919, 200980, 200600, 81010, 220410, 80820, 80540, 81190, 200870, 200840, 81310, 81320, 220510, 80590, 80719, 81020, 200830, 200850, 80940, 81040, 81350, 200710, 200791, 200892, 200899, 80910, 80920, 81050, 81110, 200880, 200891, 220430, 200911, 110630, 81120, 200939, 200969, 80550, 200961, 200931, 200949, 200979, 200929, 81060, 200912, 200921, 200941, 200971, 81070, 80310, 80390, 80830, 200989, 80840, 80929, 80921, 200897, 200893, 200981
Maize	100590, 110220, 151529, 100510, 110313, 200580, 71040, 151521, 230210
Nuts	80250, 80211, 80212, 80119, 80240, 80231, 80290, 200819, 80122, 80221, 80222, 80132, 80232, 80131, 80121, 80260, 80251, 80252, 80241, 80242, 80261, 80262, 80270, 80280

Commodities	HS codes
Other cereals	190590, 100700, 220300, 110100, 121490, 110290, 100110, 230230, 190120, 190219, 190190, 100300, 100190, 190211, 100820, 110311, 110412, 110423, 110429, 190110, 190490, 190520, 230240, 100200, 100810, 100830, 100890, 110430, 110710, 190410, 190540, 100400, 110419, 110210, 110720, 121300, 190510, 110319, 190420, 110422, 230800, 190531, 190532, 110320, 190430, 100210, 100390, 100860, 100199, 100790, 100821, 100829, 100119, 100490, 100710, 100850, 100111, 100191, 100290, 100410, 100310, 100840
Other oilseeds	151590, 120799, 150990, 151211, 151219, 210330, 120600, 120720, 120220, 120740, 151511, 151519, 120210, 120400, 230630, 230620, 151229, 230610, 151530, 151221, 120760, 230690, 120791, 151550, 120890, 120750, 120730, 151411, 120510, 120590, 230641, 230649, 151499, 151419, 151491, 120241, 120770, 70992, 120729, 120230, 120721, 80112
Palm	230660, 120999, 151190, 151321, 151329, 151110
Pulses	71390, 71331, 71332, 71333, 71339, 71350, 71340, 71310, 71320, 110610, 230250, 71360, 71335, 71334
Rice	100620, 100630, 100640, 100610
Rubber	400121, 400129, 400122, 400110, 400130
Soybeans	210390, 150790, 150710, 120100, 230400, 210610, 120810, 210310, 120110, 120190
Stimulants	90930, 121190, 330129, 90950, 330190, 91099, 90210, 90220, 90920, 121010, 130219, 330130, 90412, 91010, 90240, 90230, 90300, 330113, 91020, 330112, 330125, 90420, 121020, 330119, 330124, 91091, 90411, 90620, 90700, 90810, 90910, 210120, 90500, 90830, 91030, 90940, 90820, 90611, 90619, 90831, 90922, 90931, 90932, 90962, 91012, 90421, 90921, 90961, 91011, 90422, 90510, 90520, 90720, 90812, 90811, 90821, 90822, 90832, 90710
Sugar crops	170290, 170410, 170490, 170199, 121291, 170112, 170310, 170230, 170390, 170219, 170111, 170211, 170240, 170191, 170260, 170220, 230320, 121293, 170114, 170113

Commodities	HS codes
Vegetables	71290, 70200, 70390, 70700, 70990, 70951, 71080, 71490, 121299, 70190, 70820, 71190, 200190, 200290, 200490, 200559, 70810, 70890, 71029, 71090, 200210, 200110, 70310, 70690, 70960, 70320, 70410, 70610, 71220, 70521, 200551, 70920, 200310, 200520, 200540, 70110, 71010, 71021, 71022, 71030, 110520, 200410, 70490, 70519, 70511, 70930, 70940, 110510, 200560, 200950, 70420, 71420, 121292, 70529, 200510, 70970, 71140, 200320, 200390, 70959, 71151, 71159, 71231, 71239, 71233, 71232, 200599, 200591, 70993, 70999, 121294, 70991, 71440, 71430, 71450

A3. DeDuCe model

This model combines high-resolution spatial datasets on land cover change with agricultural statistics to estimate forest loss associated with the expansion of particular commodities globally. The DeDuCE model employs a spatial attribution approach that overlays multiple spatial datasets, including cropland extent maps, forest plantation data, pasture maps, and specific commodity maps (such as soybeans, cocoa, and oil palm), with annual tree cover loss data from the Global Forest Change dataset at 30-meter resolution. This spatial overlay identifies direct forest loss pixels attributed to land use for commodity production. When forest loss pixels cannot be spatially attributed to specific commodities, the model employs a statistical land-balance approach using FAOSTAT agricultural statistics to determine the likely drivers of deforestation based on changes in harvested areas and production. For example: if spatial attribution identifies that forest loss pixels (100 ha) are attributed to cropland expansion but cannot explicitly identify specific crops, the statistical method determines what crops have expanded in that area. If maize area expanded by 60% and soybean by 40% of total crop expansion, then 60 ha are attributed to maize and 40 ha to soybean. The model accounts for land-use change dynamics including competition between cropland and pasture, incorporating a 3-year lag period to capture delays between forest clearing and agricultural establishment.



{aa}

Figure A3.1 Accumulated deforestation attributed to selected commodities over the period 2000-2022

Source: Singh and Persson (2024)

A4. Primary commodities aggregation to commodities

Table A4.1: Aggregation of primary commodities to commodities

Commodity Group	Commodity from DeDuce Model	Products (FCL item code)
Cassava	Cassava, fresh; Cassava leaves	125, 126, 127, 128, 129
Cocoa	Cocoa beans	
Coffee	Coffee, green	656, 657, 658, 659, 660
Fibre	Seed cotton, unginned; Kenaf, and other textile bast fibres, raw or retted; Sisal, raw; Flax, processed but not spun; Other fibre crops, raw, n.e.c.; True hemp, raw or retted; Jute, raw or retted; Flax, raw or retted; Ramie, raw or retted; Agave fibres, raw, n.e.c.; Abaca, manila hemp, raw	
Fruits	Apples; Apricots; Cantaloupes and other melons; Figs; Grapes; Oranges; Other berries and fruits of the genus vaccinium n.e.c.; Other citrus fruit, n.e.c.; Other fruits, n.e.c.; Other stone fruits; Peaches and nectarines; Pears; Plums and sloes; Watermelons; Cherries; Dates; Lemons and limes; Quinces; Sour cherries; Strawberries; Tangerines, mandarins, clementines; Bananas; Pomelos and grapefruits; Pineapples; Mangoes, guavas and mangosteens; Other tropical fruits, n.e.c.; Avocados; Papayas; Blueberries; Currants; Kiwi fruit; Persimmons; Raspberries; Gooseberries; Cranberries; Plantains and cooking bananas; Cashewapple; Guavas; Mangoes; Other tropical and subtropical fruits, n.e.c.; Tangerines and mandarins; Other pome fruits; Kapok fruit	486, 489, 490, 491, 492, 495, 496, 497, 498, 499, 507, 509, 510, 512, 513, 514, 515, 517, 518, 519, 521, 523, 526, 527, 530, 531, 534, 536, 537, 541, 544, 547, 549, 550, 552, 554, 558, 560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571, 572, 574, 575, 576, 577, 580, 583, 584, 587, 591, 592, 600, 603, 604, 619, 620, 622, 623, 624, 625, 626, 628
Maize	Maize (corn); Green corn (maize)	56, 57, 58, 59, 60, 61, 446, 447, 448, 636

Commodity Group	Commodity from DeDuce Model	Products (FCL item code)
Nuts	Almonds, in shell; Chestnuts, in shell; Pistachios, in shell; Walnuts, in shell; Other nuts (excluding wild edible nuts and groundnuts), in shell, n.e.c.; Cashew nuts, in shell; Hazelnuts, in shell; Areca nuts; Kola nuts	216, 217, 220, 221, 222, 223, 224, 225, 226, 229, 230, 231, 232, 233, 234, 235
Other cereals	Barley; Millet; Wheat; Oats; Rye; Canary seed; Cereals n.e.c.; Mixed grain; Buckwheat; Fonio; Quinoa; Triticale; Sorghum	15, 16, 17, 18, 19, 20, 21, 22, 41, 44, 45, 46, 47, 48, 49, 50, 51, 71, 72, 73, 75, 76, 77, 79, 80, 81, 83, 84, 85, 89, 90, 91, 92, 94, 97, 101, 103, 104, 105, 108, 109, 110, 111, 112, 113, 114, 115, 635
Other oilseeds	Linseed; Olives; Sesame seed; Sunflower seed; Groundnuts, excluding shelled; Rape or colza seed; Castor oil seeds; Safflower seed; Other oil seeds, n.e.c.; Poppy seed; Coconuts, in shell; Karite nuts (sheanuts); Mustard seed; Melonseed; Hempseed; Tallowtree seeds; Jojoba seeds; Tung nuts	242, 249, 260, 263, 265, 266, 267, 268, 269, 270, 271, 272, 275, 276, 278, 280, 281, 282, 289, 290, 291, 292, 293, 294, 295, 296, 297, 299, 306, 311, 313, 314, 329, 331, 332, 333, 334, 335, 336, 338, 339, 340, 341, 343
Palm	Oil palm fruit; Palm nuts and kernels	256, 257, 258, 259
Pasture	Cattle meat; Leather	
Pulses	Beans, dry; Broad beans and horse beans, dry; Other pulses n.e.c.; Chick peas, dry; Lentils, dry; Peas, dry; Pigeon peas, dry; Cow peas, dry; Lupins; Vetches; Bambara beans, dry; Pulses, n.e.c.	
Rice	Rice	27, 28, 29, 30, 31, 32, 35, 36, 37, 38, 39

Commodity Group	Commodity from DeDuce Model	Products (FCL item code)
Rubber	Natural rubber in primary forms	836, 837, 839
Soybeans	Soya beans	236, 237, 238, 239, 240
Stimulants	Anise, badian, coriander, cumin, caraway, fennel and juniper berries, raw; Other stimulant, spice and aromatic crops, n.e.c.; Hop cones; Unmanufactured tobacco; Chillies and peppers, dry (Capsicum spp., Pimenta spp.), raw; Maté leaves; Peppermint, spearmint; Tea leaves; Ginger, raw; Pepper (Piper spp.), raw; Nutmeg, mace, cardamoms, raw; Cinnamon and cinnamon-tree flowers, raw; Cloves (whole stems), raw; Vanilla, raw; Pyrethrum, dried flowers; Stimulant, spice and aromatic crops, n.e.c.	
Sugar	Sugar beet; Sugar cane; Other sugar crops n.e.c.	
Vegetables	Onions and shallots, dry (excluding dehydrated); Other vegetables, fresh n.e.c.; Potatoes; Broad beans and horse beans, green; Cabbages; Carrots and turnips; Cauliflowers and broccoli; Chillies and peppers, green (Capsicum spp. and Pimenta spp.); Cucumbers and gherkins; Eggplants (aubergines); Green garlic; Leeks and other alliaceous vegetables; Lettuce and chicory; Okra; Onions and shallots, green; Other beans, green; Peas, green; Pumpkins, squash and gourds; Spinach; Tomatoes; Artichokes; String beans; Asparagus; Sweet potatoes; Taro; Yams; Chicory roots; Edible roots and tubers with high starch or inulin content, n.e.c., fresh; Yautia	358, 366, 367, 372, 373, 388, 390, 391, 392, 393, 394, 397, 399, 401, 402, 403, 406, 407, 414, 417, 420, 423, 426, 430, 449, 450, 451, 459, 460, 461, 463, 465, 466, 469, 471, 472, 473, 474, 475, 476, 116, 117, 118, 120, 121, 122, 135, 136, 137, 149, 150, 151

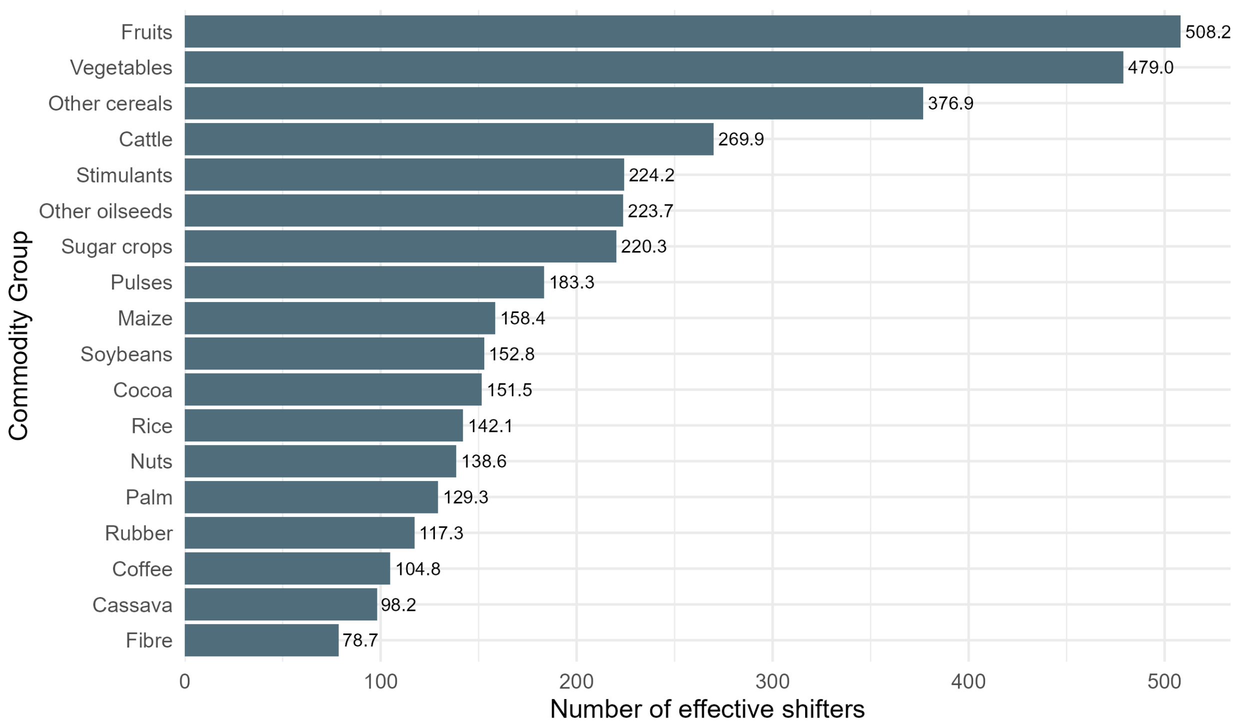
A5. Statistics of shares

Table A5.1: Descriptive statistics of shares

Commodity / Variable	Minimum	Mean	Median	Maximum	SD	N
Panel A: Total						
Share (total)	0.00000	0.00192	0.00000	1.00000	0.02318	2,111,044
Panel B: By commodities						
Cassava	0.00000	0.01558	0.00014	1.00000	0.08153	12,839
Cattle	0.00000	0.00201	0.00001	1.00000	0.02059	114,623
Cocoa	0.00000	0.00327	0.00001	1.00000	0.02948	70,107
Coffee	0.00000	0.00382	0.00001	1.00000	0.02907	59,896
Fibre	0.00000	0.00415	0.00002	1.00000	0.03529	53,736
Fruits	0.00000	0.00052	0.00000	0.94237	0.00866	439,107
Maize	0.00000	0.00585	0.00001	1.00000	0.04816	38,277
Nuts	0.00000	0.00309	0.00001	1.00000	0.03079	74,210
Other cereals	0.00000	0.00088	0.00000	0.99941	0.01235	261,766
Other oilseeds	0.00000	0.00177	0.00000	1.00000	0.02191	129,434
Palm	0.00000	0.00969	0.00007	1.00000	0.05980	22,611
Pulses	0.00000	0.00404	0.00003	1.00000	0.03440	54,911
Rice	0.00000	0.00922	0.00004	1.00000	0.05715	24,399
Rubber	0.00000	0.01151	0.00011	1.00000	0.07063	17,991
Soybeans	0.00000	0.00426	0.00001	1.00000	0.03521	54,001
Stimulants	0.00000	0.00087	0.00000	0.98030	0.01207	264,959
Sugar crops	0.00000	0.00237	0.00001	0.99467	0.02450	97,112

Commodity / Variable	Minimum	Mean	Median	Maximum	SD	N
Vegetables	0.00000	0.00072	0.00000	1.00000	0.01092	321,065

Figure A5.1: Number of effective shifters by commodity groups



Source: Own illustration

A6. Statistics of shifts

Table A6.1: Descriptive statistics of shifts

Commodity / Variable	Mean	P10	Median	P90	SD	N
Panel A: Total						
Shift (total)	8.29767	4.27667	8.57320	11.86529	2.92173	6,920,563
Panel B: By commodities						
Cassava	6.47454	2.48491	6.82329	9.53175	2.78040	29,734
Cocoa and cocoa products	9.89053	6.10702	10.28766	13.08350	2.79632	215,031
Coffee	9.40580	4.99043	10.05878	12.87376	3.01161	226,124
Fibre crops	8.09431	3.13549	8.40358	12.55261	3.52425	167,439
Fruits	8.13329	4.26268	8.33950	11.67911	2.87209	1,542,195
Maize	8.04850	4.04305	8.13535	12.00712	2.99576	162,905
Nuts	7.76191	3.40120	8.14700	11.43201	3.04384	257,304
Other cereals	8.85909	5.16479	9.10941	12.17021	2.74374	966,333
Other oilseeds	7.41397	3.46574	7.61481	11.00836	2.89482	490,566
Palm	9.44513	5.05625	9.97548	13.02262	3.13321	50,283
Pasture (Cattle meat + leather)	8.93946	5.12396	9.17585	12.56354	2.87632	161,857
Pulses and legumes	7.31647	3.55535	7.55276	10.65265	2.71470	194,117
Rice	9.12667	5.03044	9.58590	12.47222	2.82509	191,346
Rubber	8.52294	3.61092	9.09515	12.66370	3.49068	57,031
Soybeans	8.88528	4.55388	9.11295	13.03727	3.18250	107,863
Stimulants, spices and aromatic crops	7.86041	4.26268	8.06369	11.13303	2.64304	611,729
Sugar crops	8.89968	5.11199	9.34027	11.94509	2.69916	392,226

Commodity / Variable	Mean	P10	Median	P90	SD	N
Vegetables	7.97256	4.00733	8.31214	11.36130	2.82742	1,096,480

A7. First stage and instrument strength

Table A7.1: First stage regression showing the predictive power of foreign demand on exports

Interaction	FD	$\widehat{FD}$	FD	$\widehat{FD}$	FD	$\widehat{FD}$
1	0.258***	-0.471***				
	(0.008)	(0.045)				
Cassava			0.329***	-0.467**		
			(0.029)	(0.181)		
Cocoa			0.308***	-0.368		
			(0.025)	(0.264)		
Coffee			0.324***	-0.927***		
			(0.023)	(0.253)		
Fibre			0.264***	-0.630***		
			(0.017)	(0.191)		
Fruits			0.228***	-0.415***		
			(0.017)	(0.119)		
Maize			0.265***	-0.507***		
			(0.016)	(0.144)		
Nuts			0.209***	-0.017		
			(0.029)	(0.137)		
Other cereals			0.240***	-0.540***		
			(0.017)	(0.125)		
Other oilseeds			0.279***	-0.519***		

Interaction	FD	$\widehat{FD}$	FD	$\widehat{FD}$	FD	$\widehat{FD}$
			(0.015)	(0.121)		
Palm			0.249***	-0.593**		
			(0.041)	(0.253)		
Cattle			0.267***	-0.682***		
			(0.017)	(0.133)		
Pulses			0.236***	-0.393***		
			(0.015)	(0.079)		
Rice			0.285***	-0.588***		
			(0.020)	(0.126)		
Rubber			0.333***	-0.151		
			(0.050)	(0.520)		
Soybeans			0.244***	-0.575***		
			(0.020)	(0.131)		
Stimulants			0.148***	-0.111		
			(0.022)	(0.128)		
Sugar crops			0.216***	-0.470***		
			(0.018)	(0.149)		
Vegetables			0.252***	-0.614***		
			(0.015)	(0.130)		
Africa					0.278***	-0.613***
					(0.010)	(0.078)
Europe					0.203***	-0.230***

Interaction	FD	$\widehat{FD}$	FD	$\widehat{FD}$	FD	$\widehat{FD}$
					(0.018)	(0.058)
North and Central America					0.236***	-0.283**
					(0.021)	(0.102)
North Asia					0.177**	-0.147***
					(0.065)	(0.049)
Oceania					0.305***	-0.483*
					(0.045)	(0.247)
Rest of Asia					0.234***	-0.522***
					(0.016)	(0.082)
South America					0.284***	-0.607***
					(0.020)	(0.126)
Southeast Asia					0.254***	-0.415***
					(0.016)	(0.104)
N	41677	41677	41677	41677	41677	41677
R-squared	0.770	0.667	0.774	0.668	0.771	0.667

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

Note: Estimates are based on interaction between instruments and variables in first column. The columns represents the results of separate regression. The country-year and commodity-fixed effects are taken.

Table A7.2: Commodity-level prediction of foreign demand on export

	Foreign Demand (FD)			$\widehat{FD}$		
Group	Estimate	N	R-squared	Estimate	N	R-squared
Cassava	0.156*** (0.032)	1325	0.854	-0.096 (0.072)	1325	0.834
Cocoa	0.087*** (0.017)	1129	0.920	-0.017 (0.043)	1129	0.913
Coffee	0.134*** (0.017)	1459	0.930	-0.100** (0.036)	1459	0.918
Fibre	0.136*** (0.014)	2399	0.861	-0.073 (0.066)	2399	0.838
Fruits	0.141*** (0.018)	3423	0.942	-0.168** (0.066)	3423	0.927
Maize	0.113*** (0.016)	2717	0.856	-0.132** (0.059)	2717	0.843
Nuts	0.100*** (0.028)	2275	0.842	-0.248*** (0.077)	2275	0.834
Other cereals	0.102*** (0.019)	2857	0.903	-0.081 (0.066)	2857	0.895
Other oilseeds	0.126*** (0.012)	3196	0.906	-0.205*** (0.063)	3196	0.892
Palm	0.070*** (0.020)	1053	0.869	-0.193*** (0.044)	1053	0.864
Cattle	0.121*** (0.024)	3180	0.919	-0.134*** (0.039)	3180	0.907
Pulses	0.124*** (0.015)	2898	0.868	-0.186*** (0.055)	2898	0.852

	Foreign Demand (FD)			$\widehat{FD}$		
Group	Estimate	N	R-squared	Estimate	N	R-squared
Rice	0.135*** (0.019)	2085	0.799	-0.221*** (0.068)	2085	0.781
Rubber	0.159*** (0.027)	630	0.934	-0.053 (0.067)	630	0.901
Soybeans	0.137*** (0.019)	2086	0.891	-0.169** (0.069)	2086	0.874
Stimulants	0.109*** (0.012)	2941	0.934	-0.153** (0.069)	2941	0.924
Sugar crops	0.158*** (0.019)	2639	0.863	-0.219*** (0.070)	2639	0.838
Vegetables	0.140*** (0.012)	3385	0.930	-0.209** (0.077)	3385	0.916
Africa	0.255*** (0.010)	12199	0.714	-0.538*** (0.074)	12199	0.594
Europe	0.190*** (0.019)	8174	0.853	-0.281*** (0.050)	8174	0.799
North and Central America	0.215*** (0.019)	5177	0.823	-0.278*** (0.084)	5177	0.769
North Asia	0.186** (0.038)	1104	0.859	-0.258* (0.089)	1104	0.821
Oceania	0.293*** (0.032)	1561	0.833	-0.475** (0.182)	1561	0.736
Rest of Asia	0.204*** (0.014)	5873	0.769	-0.407*** (0.069)	5873	0.690

	Foreign Demand (FD)			$\widehat{FD}$		
Group	Estimate	N	R-squared	Estimate	N	R-squared
South America	0.293*** (0.022)	4278	0.767	-0.705*** (0.133)	4278	0.630
Southeast Asia	0.255*** (0.017)	3311	0.789	-0.420*** (0.092)	3311	0.692

Note: Estimates are based on individual regressions of exports on foreign demand, country fixed effects and yearly fixed effects. Standard errors are clustered at countries and years level.

A9. Bootstrap procedure

We obtain inference for the CF–PPML estimator via a block bootstrap aligned with the panel structure of the data. The full-sample control-function (CF) model is first estimated as described in the empirical strategy section, using the same country-by-year and commodity-by-year fixed effects in both stages.

- **First stage:** We regress $\log X_{ikt}$ on FD_{ikt} and the fixed effects to produce residuals $\widehat{\nu}_{ikt}$.
- **Second stage:** We estimate the PPML including $\log X_{ikt}$, $\widehat{\nu}_{ikt}$, and the same fixed effects, yielding estimates of $\widehat{\alpha}$ (the elasticity of deforestation with respect to foreign demand/exports) and $\widehat{\delta}$ (the control-function coefficient used for the endogeneity test).

Resampling proceeds by treating each country–commodity panel (i, k) as a block containing its complete time series. Our dataset consists of 2001 such blocks. For each bootstrap replication, we sample, with replacement, 2001 blocks (the same number as in the original data), stack the selected panels to form the bootstrap sample (allowing duplicates), and re-estimate both stages exactly as in the full-sample procedure, recomputing the first-stage residuals within the bootstrap sample. We repeat this 1000 times, and use the resulting covariance matrix of the bootstrap draws to obtain "bootstrap standard errors" for $\widehat{\alpha}$ and $\widehat{\delta}$:

$$\widehat{\mathrm{SE}}_{\mathrm{boot}}(\widehat{\alpha}) = \sqrt{\widehat{\mathrm{Var}}_{\mathrm{boot}}(\widehat{\alpha})}, \qquad \widehat{\mathrm{SE}}_{\mathrm{boot}}(\widehat{\delta}) = \sqrt{\widehat{\mathrm{Var}}_{\mathrm{boot}}(\widehat{\delta})}.$$

In our main results, we report these bootstrap-based standard errors together with significance stars derived from the same bootstrap distribution. For each coefficient (e.g. $\widehat{\alpha}$), we construct its empirical bootstrap distribution, center this distribution on the full-sample estimate, and compute a two-sided bootstrap p-value as

$$p_{\mathrm{boot}}(\widehat{\alpha}) = 2 \times \min\left\{ \Pr(\tilde{\alpha}^* \leq 0),\ \Pr(\tilde{\alpha}^* \geq 0)\right\},$$

where $\tilde{\alpha}^*$ denotes draws from the centered bootstrap distribution of $\widehat{\alpha}$, and the probabilities are calculated as empirical proportions over the 1000 replications. The same procedure is applied to $\widehat{\delta}$. Significance stars in the results are then assigned according to these bootstrap p-values: $***$ if $p_{\mathrm{boot}} < 0.01$, $**$ if $p_{\mathrm{boot}} < 0.05$, $*$ if $p_{\mathrm{boot}} < 0.10$, and no star otherwise. Because both the 95% confidence intervals and the p-values are derived from the same bootstrap distribution (via percentiles and tail probabilities, respectively), a coefficient whose 95% bootstrap percentile interval excludes zero will correspondingly receive at least two stars ($**$). This block bootstrap design preserves within-panel serial correlation and arbitrary heteroskedasticity and is consistent with our maintained assumption that unobserved shocks are most strongly correlated within country–commodity panels over time.

A10. Panel structure of country-commodity

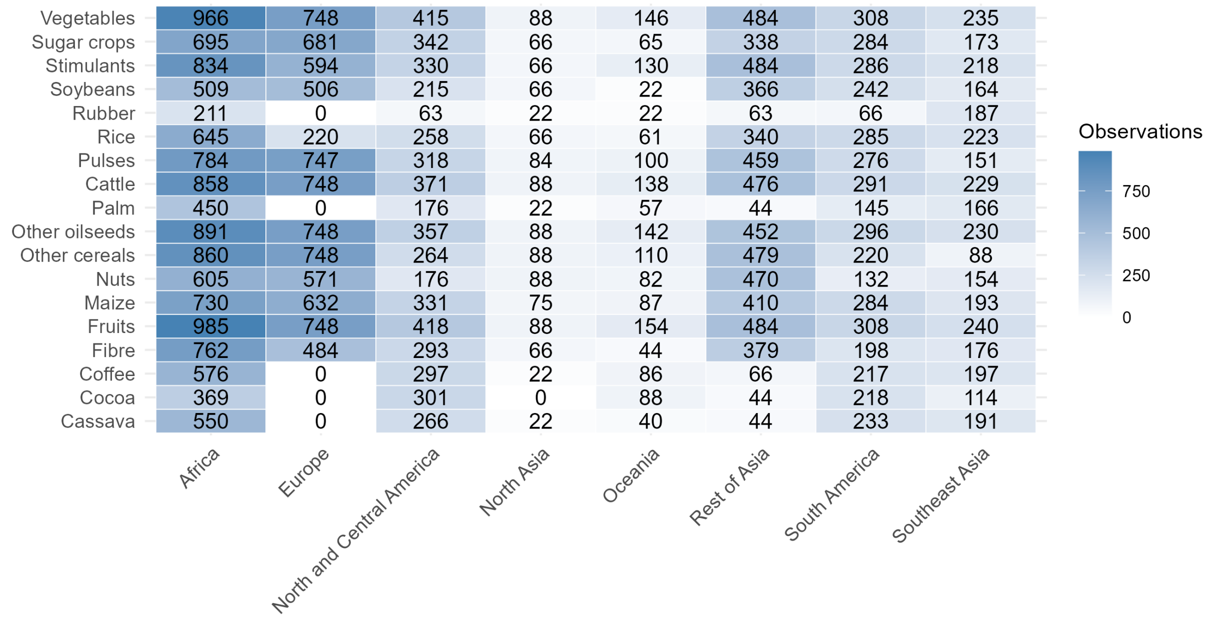


Figure A10.1: Number of observations by continent and commodity group

Source: Own illustration

A11. Specifications to estimate effects of foreign demand

The followings are the four specifications to estimate the effects of foreign demand on deforestation.

Specification 1: Pooled effect estimation:

$$C_{ikt} = \exp(\beta FD_{ik,t-1} + \beta_{it} + \beta_{kt})\varepsilon_{ikt}. \qquad (A11.1)$$

Specification 2: Heterogeneous effect by commodity group: Let $g \in G$ index commodity groups and $\mathbb{1}_{k=g}$ be the indicator for group g. Then:

$$C_{ikt} = \exp(\sum_{g \in G} \beta_g FD_{ik,t-1} \mathbb{1}_{k=g} + \beta_{it} + \beta_{kt})\varepsilon_{ikt}. \qquad (A11.2)$$

Specification 3: Heterogeneous effect by continent: Let $r(i) \in R$ index continent of country i and and $\mathbb{1}_{r(i)=r}$ be the indicator for continent r. Then:

$$C_{ikt} = \exp(\sum_{r \in R} \beta_r FD_{ik,t-1} \mathbb{1}_{r(i)=r} + \beta_{it} + \beta_{kt})\varepsilon_{ikt}. \qquad (A11.3)$$

Specification 4: Heterogeneous effect by continent-commodity pair:

$$C_{ikt} = \exp(\sum_{g \in G} \sum_{r \in R} \beta_{gr} FD_{ik,t-1} \mathbb{1}_{k=g} \mathbb{1}_{r(i)=r} + \beta_{it} + \beta_{kt})\varepsilon_{ikt}. \qquad (A11.4)$$

A12. Specifications to estimate effects of export sales

First, we estimate the first-stage estimation as shown in equation (8). Then, we estimate the residuals from first-stage, and then use it in second stage regression, which is called as two-stage residual inclusion (2-SRI).

Specification 1: Pooled effect estimation:

$$C_{ikt} = \exp(\alpha log X_{ikt} + \alpha_{it} + \alpha_{kt} + \delta \widehat{\nu_{ikt}})\varepsilon_{ikt}. \qquad (A12.1)$$

Specification 2: Heterogeneous effect by commodity group: Let $g \in G$ index commodity groups and $\mathbb{1}_{k=g}$ be the indicator for group g. Then:

$$C_{ikt} = \exp(\sum_{g\in G} \alpha_g log X_{ikt} \mathbb{1}_{k=g} + \alpha_{it} + \alpha_{kt} + \delta \widehat{\nu_{ikt}})\varepsilon_{ikt}. \qquad (A12.2)$$

Specification 3: Heterogeneous effect by continent: Let $r(i) \in R$ index continent of country i and and $\mathbb{1}_{r(i)=r}$ be the indicator for continent r. Then:

$$C_{ikt} = \exp(\sum_{r\in R} \alpha_r log X_{ikt} \mathbb{1}_{r(i)=r} + \alpha_{it} + \alpha_{kt} + \delta \widehat{\nu_{ikt}})\varepsilon_{ikt}. \qquad (A12.3)$$

Specification 4: Heterogeneous effect by continent-commodity pair:

$$C_{ikt} = \exp(\sum_{g\in G}\sum_{r\in R} \alpha_{gr} log X_{ikt} \mathbb{1}_{k=g} \mathbb{1}_{r(i)=r} + \alpha_{it} + \alpha_{kt} + \delta \widehat{\nu_{ikt}})\varepsilon_{ikt}. \qquad (A12.4)$$

A13. Sensitivity checks

A13.1 Effects of foreign demand on deforestation

Table A13.1.1. Effect of foreign demand on deforestation across multiple forms of deforestation

	log(def)	log(def+1)	asinh(def)	Level
Foreign Demand	0.066	0.061***	0.066***	381.227
	(0.041)	(0.016)	(0.018)	(245.250)
Observations	33562	41677	41677	41677
R-squared	0.361	0.535	0.531	0.101
Country × Year FE	X	X	X	X
Commodity × Year FE	X	X	X	X

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

Notes: Standard errors clustered by country, commodity and year in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13.1.2. Effect of foreign demand on deforestation by commodity across multiple forms of deforestation

	log(def)	log(def+1)	asinh(def)	Level
Cassava × FD	0.017	-0.005	-0.005	-566.237
	(0.117)	(0.048)	(0.051)	(358.265)
Cocoa × FD	0.174	0.135***	0.145***	47.169
	(0.162)	(0.046)	(0.049)	(267.465)
Coffee × FD	0.361**	0.125***	0.137***	-146.698
	(0.139)	(0.035)	(0.037)	(199.625)
Fibre × FD	0.120	0.032	0.036	-221.277
	(0.089)	(0.020)	(0.021)	(218.354)
Fruits × FD	0.096**	0.032	0.036	65.412
	(0.036)	(0.020)	(0.021)	(66.830)
Maize × FD	-0.058	0.028	0.031	-14.331
	(0.080)	(0.020)	(0.022)	(81.647)
Nuts × FD	-0.104	0.059*	0.064*	-132.192
	(0.095)	(0.033)	(0.035)	(209.927)
Other cereals × FD	0.126	0.060*	0.066*	235.227
	(0.081)	(0.031)	(0.034)	(185.416)
Other oilseeds × FD	0.139***	0.117***	0.129***	265.561
	(0.041)	(0.019)	(0.020)	(168.366)
Palm × FD	0.248**	0.223***	0.237***	2836.786
	(0.108)	(0.066)	(0.069)	(2593.877)
Cattle × FD	0.105**	0.023	0.019	2910.382

	log(def)	log(def+1)	asinh(def)	Level
	(0.042)	(0.036)	(0.039)	(2617.015)
Pulses × FD	0.157**	0.072***	0.081***	167.090
	(0.068)	(0.023)	(0.026)	(174.214)
Rice × FD	-0.075	0.017	0.018	87.887
	(0.105)	(0.029)	(0.032)	(99.931)
Rubber × FD	0.349***	0.373***	0.391***	2644.697**
	(0.097)	(0.074)	(0.077)	(1086.286)
Soybeans × FD	-0.101	0.039	0.040	345.912
	(0.104)	(0.033)	(0.036)	(204.986)
Stimulants × FD	-0.044	0.035	0.038	-52.776
	(0.094)	(0.030)	(0.033)	(78.221)
Sugar × FD	-0.291**	0.037*	0.037*	221.806
	(0.121)	(0.019)	(0.021)	(194.237)
Vegetables × FD	0.068	0.006	0.008	158.441
	(0.040)	(0.018)	(0.019)	(202.051)
Observations	33562	41677	41677	41677
R-squared	0.365	0.541	0.538	0.112
Country-Year FE	X	X	X	X
Commodity-Year FE	X	X	X	X

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

Notes: Standard errors clustered by country and year in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A13.1.3. Effect of foreign demand on deforestation by continent across multiple forms of deforestation

	Deforestation			
	log(def)	log(def+1)	asinh(def)	Level
Africa x FD	0.118***	0.072***	0.078***	198.486
	(0.033)	(0.017)	(0.018)	(128.295)
Europe x FD	-0.171*	-0.016	-0.018	-135.948
	(0.089)	(0.023)	(0.026)	(110.168)
North and Central America x FD	-0.006	0.069***	0.073***	202.041**
	(0.071)	(0.023)	(0.025)	(87.515)
North Asia x FD	-0.318**	-0.046	-0.054	-170.276
	(0.140)	(0.027)	(0.031)	(236.247)
Oceania x FD	0.172**	0.087***	0.094***	9.752
	(0.077)	(0.029)	(0.032)	(125.771)
Rest of Asia x FD	0.115**	0.047***	0.054***	13.084
	(0.051)	(0.016)	(0.018)	(70.534)
South America x FD	0.103*	0.088***	0.093***	2090.058
	(0.051)	(0.023)	(0.024)	(1553.984)
Southeast x FD	0.047	0.091	0.094	883.856*
	(0.096)	(0.057)	(0.060)	(463.456)
Observations	33562	41677	41677	41677
R-squared	0.363	0.536	0.532	0.105
Country-Year FE	X	X	X	X
Commodity-Year FE	X	X	X	X

	Deforestation			
	log(def)	log(def+1)	asinh(def)	Level

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

Notes: Standard errors clustered by country and year in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

A13.2 Effects of export sales on deforestation

Table A13.2.1. Effect of export sales on deforestation across multiple form of deforestation

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Exports)	120.848	0.189	0.145***	0.160***	976.648	0.161**	0.156***	0.168***
	(300.975)	(0.163)	(0.048)	(0.052)	(603.581)	(0.070)	(0.026)	(0.028)
Observations	41677	33562	41677	41677	41677	33562	41677	41677
R-squared	0.100	0.366	0.552	0.549	0.102	0.366	0.553	0.549
Country-Year FE	X	X	X	X	X	X	X	X
Commodity-Year FE	X	X	X	X	X	X	X	X
Wu-Hausman stat	1.59	1.84	3.91**	3.65*	0.34	61.88***	74.76***	76.64***

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

Notes: Standard errors clustered by country and year in parentheses. All models use 2SLS with country-year and commodity-year fixed effects. Columns (1)-(4) instrument exports with $\widehat{FD}$; columns (5)-(8) instrument with FD. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A13.2.2. Effect of export sales on deforestation by commodity across multiple forms of deforestation

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cassava × log(Exports)	-1015.518	-0.080	-0.062	-0.061	-1785.496*	-0.173	-0.151	-0.152
	(658.566)	(0.206)	(0.082)	(0.088)	(981.676)	(0.238)	(0.093)	(0.100)
Cocoa × log(Exports)	-274.297	0.305	0.118	0.130	-1078.240	0.171	-0.022	-0.019
	(722.981)	(0.258)	(0.086)	(0.092)	(1101.008)	(0.249)	(0.095)	(0.103)
Coffee × log(Exports)	-255.895	0.434*	0.156**	0.171**	-904.379	0.153	0.043	0.050
	(368.648)	(0.240)	(0.069)	(0.075)	(784.158)	(0.278)	(0.077)	(0.083)
Fibre × log(Exports)	83.759	0.076	0.082*	0.090*	-208.267	0.000	0.086	0.094
	(150.881)	(0.143)	(0.041)	(0.044)	(368.137)	(0.196)	(0.066)	(0.070)
Fruits × log(Exports)	511.289	0.232***	0.153***	0.165***	-11.365	0.303*	0.172***	0.186***
	(310.350)	(0.079)	(0.037)	(0.040)	(242.728)	(0.167)	(0.053)	(0.057)

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Maize × log(Exports)	406.364	-0.020	0.133***	0.143***	-21.662	0.052	0.157**	0.171**
	(304.607)	(0.137)	(0.042)	(0.045)	(287.547)	(0.206)	(0.068)	(0.075)
Nuts × log(Exports)	18.161	0.044	0.163**	0.181**	-389.793	0.140	0.166**	0.189**
	(202.038)	(0.178)	(0.062)	(0.067)	(421.750)	(0.234)	(0.075)	(0.081)
Other cereals × log(Exports)	666.863*	0.376**	0.272***	0.293***	137.695	0.585***	0.357***	0.387***
	(340.349)	(0.134)	(0.054)	(0.058)	(286.125)	(0.192)	(0.065)	(0.070)
Other oilseeds × log(Exports)	630.377*	0.314***	0.275***	0.300***	-22.253	0.391**	0.279***	0.308***
	(346.433)	(0.077)	(0.035)	(0.038)	(277.177)	(0.164)	(0.060)	(0.064)
Palm × log(Exports)	4221.289	0.210	0.271**	0.290**	3113.741	0.117	0.204	0.222
	(4038.235)	(0.148)	(0.120)	(0.127)	(3871.097)	(0.240)	(0.144)	(0.155)
Cattle × log(Exports)	5906.387	0.230***	0.126**	0.121*	5239.514	0.328*	0.139*	0.133*

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(5018.760)	(0.077)	(0.055)	(0.059)	(4513.062)	(0.170)	(0.069)	(0.075)
Pulses × log(Exports)	446.666	0.382***	0.210***	0.233***	-153.522	0.481**	0.234***	0.261***
	(324.778)	(0.125)	(0.046)	(0.050)	(303.328)	(0.205)	(0.065)	(0.070)
Rice × log(Exports)	343.570	-0.074	0.098*	0.105*	-285.133	-0.031	0.122*	0.132*
	(236.654)	(0.171)	(0.053)	(0.058)	(393.337)	(0.218)	(0.070)	(0.076)
Rubber × log(Exports)	3019.882**	0.629***	0.701***	0.737***	747.528	0.463*	0.488***	0.514***
	(1338.515)	(0.160)	(0.131)	(0.137)	(2060.159)	(0.224)	(0.168)	(0.175)
Soybeans × log(Exports)	1183.830	0.176	0.207***	0.221***	881.707	0.355	0.273***	0.294***
	(714.435)	(0.179)	(0.058)	(0.062)	(615.791)	(0.261)	(0.078)	(0.083)
Stimulants × log(Exports)	386.911	0.114	0.162***	0.176***	-93.603	0.137	0.175**	0.191**
	(225.575)	(0.142)	(0.051)	(0.057)	(294.017)	(0.195)	(0.067)	(0.073)

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sugar × log(Exports)	575.902	-0.264	0.126***	0.133***	4.729	-0.146	0.154**	0.164**
	(386.922)	(0.174)	(0.036)	(0.039)	(276.934)	(0.238)	(0.059)	(0.064)
Vegetables × log(Exports)	542.902	0.186**	0.115***	0.126***	-35.168	0.269	0.139**	0.154**
	(365.016)	(0.082)	(0.033)	(0.036)	(261.803)	(0.172)	(0.052)	(0.057)
Observations	41677	33562	41677	41677	41677	33562	41677	41677
R-squared	0.119	0.364	0.542	0.538	0.113	0.364	0.539	0.535
Country-Year FE	X	X	X	X	X	X	X	X
Commodity-Year FE	X	X	X	X	X	X	X	X

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

Notes: Standard errors clustered by country and year in parentheses. All models use 2SLS with country-year and commodity-year fixed effects. Columns (1)-(4) instrument exports with $\widehat{FD}$; columns (5)-(8) instrument with FD. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A13.2.3. Effect of export sales on deforestation by continent across multiple forms of deforestation

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Africa × log(Exports)	339.613	0.122	0.126***	0.138***	-589.809	-0.147	0.010	0.015
	(328.695)	(0.091)	(0.039)	(0.042)	(448.526)	(0.175)	(0.058)	(0.064)
Europe × log(Exports)	50.433	0.124	0.063	0.068	-518.779	0.358	0.094	0.100
	(130.135)	(0.152)	(0.046)	(0.051)	(522.437)	(0.240)	(0.065)	(0.071)
North & Central America × log(Exports)	558.570**	0.205	0.185***	0.198***	35.209	0.520**	0.229***	0.253***
	(232.001)	(0.134)	(0.054)	(0.059)	(340.397)	(0.213)	(0.075)	(0.082)
North Asia × log(Exports)	181.529	-0.391	0.157	0.154	12.133	0.009	0.365**	0.376**
	(340.876)	(0.248)	(0.094)	(0.101)	(460.351)	(0.278)	(0.133)	(0.140)
Oceania × log(Exports)	123.930	0.397**	0.223***	0.237***	25.101	0.387	0.311***	0.326***

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(205.109)	(0.175)	(0.070)	(0.074)	(419.119)	(0.249)	(0.109)	(0.114)
Rest of Asia × log(Exports)	191.734	0.279**	0.141***	0.159***	-393.141	0.350	0.186***	0.215***
	(148.301)	(0.130)	(0.040)	(0.044)	(447.614)	(0.221)	(0.066)	(0.072)
South America × log(Exports)	5343.558	0.319***	0.264***	0.278***	3278.416	0.495*	0.266***	0.284***
	(3805.245)	(0.100)	(0.054)	(0.055)	(2000.339)	(0.255)	(0.082)	(0.088)
Southeast Asia × log(Exports)	2214.072*	-0.231	0.235**	0.240*	227.168	-0.182	0.176*	0.184*
	(1130.589)	(0.165)	(0.110)	(0.117)	(413.255)	(0.212)	(0.097)	(0.105)
Observations	41677	33562	41677	41677	41677	33562	41677	41677
R-squared	0.106	0.362	0.535	0.532	0.101	0.362	0.532	0.529
Country-Year FE	X	X	X	X	X	X	X	X
Commodity-Year FE	X	X	X	X	X	X	X	X

	Level	log(def)	log(def+1)	asinh(def)	Level	log(def)	log(def+1)	asinh(def)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

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

Notes: Standard errors clustered by country and year in parentheses. All models use 2SLS with country-year and commodity-year fixed effects. Columns (1)-(4) instrument exports with $\widehat{FD}$; columns (5)-(8) instrument with FD. * p < 0.1, ** p < 0.05, *** p < 0.01.

A14. Back-of-envelope calculations of deforestation caused by export sales and foreign demand

We proceed in three steps to quantify the contribution of foreign demand and export growth to deforestation.

(i) First, we estimate conditional means from equations (A11.4) and (A12.4).

$$\hat{\mu}_{ikt}^{FD} \;=\; \mathbb{E}[C_{ikt} \mid \cdot] \;=\; \exp\Big(\alpha_{it} + \alpha_{kt} + \beta_{gr}\, FD_{ik,t-1}\Big), \quad (k \in g,\; r(i) = r). \tag{A14.1}$$

$$\hat{\mu}_{ikt}^{X} \;=\; \exp\Big(\alpha_{it} + \alpha_{kt} + \alpha_{gr}\, \log X_{ikt} + \delta\, \hat{\nu}_{ikt}\Big). \tag{A14.2}$$

(ii) Then, we construct counterfactual means holding the foreign demand and exports at its baseline $t_0 = 2001$, keeping fixed effects and the CF residual unchanged.

$$\hat{\mu}_{ikt}^{FD,0} \;=\; \exp\Big(\alpha_{it} + \alpha_{kt} + \beta_{gr}\, FD_{ik,t_0-1}\Big). \tag{A14.3}$$

$$\hat{\mu}_{ikt}^{X,0} \;=\; \exp\Big(\alpha_{it} + \alpha_{kt} + \alpha_{gr}\, \log X_{ik,t_0} + \delta\, \hat{\nu}_{ikt}\Big). \tag{A14.4}$$

(iii) Now, we compute the attributable share and area.

Using the log link, the fixed effects (and CF residual) cancel in the ratio. Let $\Delta FD_{ik,t-1} \equiv FD_{ik,t-1} - FD_{ik,t_0-1}$ and $\Delta log X_{ik,t} \equiv log X_{ikt} - log X_{ik,t_0}$.

$$s_{ikt}^{FD} \;\equiv\; 1 - \frac{\hat{\mu}_{ikt}^{FD,0}}{\hat{\mu}_{ikt}^{FD}} \;=\; 1 - \exp\big(-\beta_{gr}\, \Delta FD_{ik,t-1}\big), \tag{A14.5}$$

$$s_{ikt}^{X} \;\equiv\; 1 - \frac{\hat{\mu}_{ikt}^{X,0}}{\hat{\mu}_{ikt}^{X}} \;=\; 1 - \exp\big(-\alpha_{gr}\, \Delta \log X_{ik,t} \big). \tag{A14.6}$$

Now, we translate shares into hectares using observed deforestation C_{ikt}:

$$A_{ikt}^{FD} \;=\; C_{ikt}\, s_{ikt}^{FD}, \qquad A_{ikt}^{X} \;=\; C_{ikt}\, s_{ikt}^{X}. \tag{A14.7}$$

Finally, we aggregate over (i, k) and $t \in [2002, 2022]$ and divide by 10^6 to report million hectares (Mha):

$$A_{\text{total}}^{(\cdot)} \;=\; \frac{1}{10^6} \sum_{i,k,t} A_{ikt}^{(\cdot)} \quad \text{(Mha)}. \tag{A14.8}$$