Crop prices and deforestation in the tropics

Nicolas Berman, Mathieu Couttenier, Antoine Leblois, Raphaël Soubeyran

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Abstract

Understanding the mechanisms of deforestation is necessary in order to slow or arrest its progress. To accomplish this requires rigorously estimating the demand for deforestation. We contribute to this endeavor by estimating the effect of crop prices on the demand for conversion of land from forest to agriculture in the tropics during the 21st century. The two main difficulties involved are the lack of harmonized data on local crop prices in the tropics and the fact that they are determined simultaneously with decisions to deforest. We propose a strategy to circumvent these two issues using high-resolution annual forest loss data for the tropics, combined with information on crop-specific agricultural suitability and annual international crop prices. We find that crop price variation has a significant impact on deforestation: increases in crop prices are estimated to be responsible for one-third of total deforestation in the tropics (totaling about 2 million km^2) during the period 2001-2018. We also find that the degree of openness to international trade and the level of economic development are first-order local characteristics affecting the magnitude of the impact of crop prices on deforestation.

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1 Introduction

Tropical deforestation is one of the main causes of global environmental degradation. Recent estimates indicate that food systems are responsible for a third of global anthropogenic GHG emissions (Crippa et al., 2021). It has been estimated that 17% of tropical moist forests have disappeared since 1990, and of the remaining one billion hectares (as of 2019), 10% are degraded (Vancutsem et al., 2021). Deforestation threatens crucial ecosystem services, such as biodiversity richness, climate regulation, carbon storage and water supplies, and encourages the spread of infectious diseases.[1] Forests not only provide private goods such as timber and non-timber products and local public goods in the form of watersheds, erosion control, nutrient recycling and local climate effects, but also global public goods such as carbon storage and biodiversity (see, for example, Sandler 1993). The main market failure involved arises from the nature of these global public goods and the presence of positive externalities, whereby the preservation efforts of one country also benefit other countries. Moreover, market forces appear to be among the most important factors driving the agricultural expansion (Angelsen, 1999; Pendrill et al., 2019) that leads to tropical deforestation (Geist and Lambin, 2002; Curtis et al., 2018; Balboni et al., 2022). Forecasts predict a sharp increase in food demand in coming decades, with projected growth of at least 50% by 2050 (Fukase and Martin, 2020; FAO, 2017). This will clearly drive crop prices up and will also likely lead to a strong increase in the demand for land, and in the private value of agricultural land (Souza-Rodrigues, 2019).

We seek to estimate the effect of changes in crop prices on deforestation in the tropics. We combine various datasets for the tropical regions at the spatial resolution of 0.5-degree latitude and longitude grid cells (approximately 55 $\times$ 55 kilometers at the equator) for the period 2001-2018. We first make use of fine-grained estimates of yearly deforestation at the level of 1 arc-second pixels (approximately 30 meters $\times$ 30 meters at the equator, Hansen et al., 2013). For each cell, we compute the total number of pixels that are deforested in each year. We then gather cell-specific information on the agronomic suitability of 15 crops in order to proxy the potential crop specialization at the cell level (Global Agro- Ecological Zones, GAEZ hereafter, Fischer et al., 2012). We combine these data with the international prices of crops traded on international markets in order to construct a cell-specific, time-varying crop price index. This index is computed as the weighted sum of international crop prices in a given year, weighted by the relative agronomic suitability of each crop in the cell.[2] Our final sample includes around 12,000 cells of 0.5 $\times$ 0.5 degree for the period 2001-2018.

This strategy makes it possible to estimate the effect of local crop prices on local deforestation while taking into account the threat of simultaneity between the conversion of forest land to agriculture and local crop prices, in the absence of harmonized data on local crop prices. It exploits within-cell variation in the international crop price index and in deforestation over time. We control for a large array of unobserved factors, including all time-invariant cell characteristics, national time-varying shocks that might correlate with both deforestation and international crop prices, and local shocks such as weather

[1] See Foley et al. (2005); Turner et al. (2007); Le Quéré et al. (2016); Alkama and Cescatti (2016); Song et al. (2018); Chaves et al. (2020); Tollefson (2020).

[2] See Section 3.1 and the Online Appendix, hereafter OA, – Section OA1.1 and OA1.2.

fluctuations. We find that changes in crop prices significantly affect deforestation in the tropics and that the effect is sizable: our baseline estimates imply that the increase in our price index during the sample period explains around one third of the total deforestation observed in the tropics during that period (i.e. approximately 2 million km^2). The effect of crop price variation on deforestation increases significantly with initial forest cover, and also depends on cell-specific characteristics. The effect is more pronounced in cells more open to international trade (proxied by the distance to a seaport), in less wealthy cells (proxied by nighttime luminosity in 2000) and, to a lesser extent, in cells with weaker state capacity (proxied by the distance to the capital city). The results are robust to a variety of sensitivity tests, including the use of different estimators, standard errors adjustments, alternative definitions of the canopy threshold, inclusion of additional controls that may affect both deforestation and prices, and the exclusion of large traders that might be influencing world commodity prices. While we cannot totally rule out that the results may be partly driven by a direct effect, such that international prices directly affect the deforestation decisions of actors such as multinationals or local land managers, we nonetheless provide suggestive evidence that they are driven by an indirect effect, such that international prices affect deforestation by way of local prices. Using data on a sub-sample of countries and crops, we find that local crop prices indeed correlate substantially with international prices. We interpret the results to be demand-driven, based on a number of robustness checks which suggest that the supply conditions in large producers do not affect the estimates. This interpretation is further supported by the results which remain qualitatively similar when using a measure of foreign demand based on changes in foreign imports, rather than our international price index. Hence, our results suggest that changes in global demand and modifications of individual preferences may be having a strong impact on deforestation levels.

The paper contributes to the literature in various dimensions. First, it is the first attempt to estimate the effect of crop prices on deforestation at the local level on a global scale. While the idea that crop prices, driven by expanding global demand, are contributing to tropical deforestation is not new (Angelsen, 1999; Angelsen and Kaimowitz, 1999; Angelsen, 2010; Rudel et al., 2009; Busch and Ferretti-Gallon, 2017), the empirical evidence to date has a number of drawbacks (Pendrill et al., 2022).[3] The usual approaches in the studies carried out on a global scale include spatial attribution, input-output models, and trade and land-balance models.[4] These approaches typically use supply-side models at the national level and downscale national trade or production data to the local level. Second, by using worldwide information on agricultural suitability based on resource limitations (plant eco-physiological characteristics, climatic and edaphic requirements of crops), our approach is more tractable and is able to overcome the absence of fine-grained information on local prices in many countries.[5] Third, our methodology is agnostic in terms

[3]For studies based on cross-national comparisons, see Angelsen and Kaimowitz (1999); Rudel et al. (2009); DeFries et al. (2010); Hosonuma et al. (2012); Ordway et al. (2017); Leblois et al. (2017). For studies based on a single country or region see Barbier and Burgess (1996); Gaveau et al. (2009); Wheeler et al. (2013); Hargrave and Kis-Katos (2013); Assunção et al. (2015); Faria and Almeida (2016); Doggart et al. (2020); Harding et al. (2021); Fehlenberg et al. (2017); Ordway et al. (2017); Lundberg and Abman (2021) or on a limited number of commodities, see Goldman et al. (2020).

[4]For studies based on spatial attribution, see Goldman et al. (2020); Curtis et al. (2018); Austin et al. (2019); for studies based on input-output models, see Godar et al. (2015); Green et al. (2019); Hoang and Kanemoto (2021); and for studies based on trade and land-balance models, see Pendrill et al. (2019); Henders et al. (2015); Pendrill et al. (2019).

[5]National datasets have well-known limitations. For example, they are subject to omission bias stemming from undeclared activities, such as home-based and locally-consumed agricultural production. Thus, a large share of small-holder production is consumed locally rather than being traded on international markets, such as oil in Sub-Saharan Africa (Ordway et al., 2019).

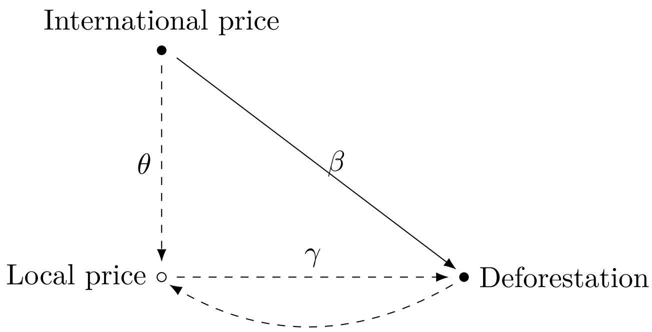
of scale of agricultural production, in contrast to studies based on spatial attribution or classification methods, which attribute large-scale commodity-driven deforestation to shifting agriculture (Curtis et al., 2018; Austin et al., 2019).[6] Fourth, it makes use of a sample of areas that were forested at the beginning of the sample period, rather than only deforested areas at the end, thus facilitating causal interpretation. Fifth, our empirical approach, which combines exogenous local crop suitability with global crop prices, allows us to control for a wide range of potential confounding factors not accounted for in previous studies. Finally, we highlight a number of policy-relevant local factors that affect the way in which fluctuations in crop prices trigger deforestation.

The remainder of the paper is organized as follows. Section 2 discusses the potential mechanisms while Section 3 describes the data and the empirical strategy. Section 4 presents the results. Section 5 presents the sensitivity analysis and discusses at length the interpretation of the results. Section 6 concludes.

2 The effect of crop prices on local deforestation – mechanisms

Average effect. International crop prices may affect local deforestation through several channels which are summarized in the directed acyclic graph in Figure 1: international crop prices may directly affect the land use decisions of local producers (β) or indirectly through local prices (θ, γ); local crop prices may affect deforestation (γ) and deforestation may affect local crop prices.

Figure 1: Directed Acyclic Graph - crop prices and deforestation



Note: Solid dots denote observed variables, circles denote unobserved variables, arrows denote robust statistical link, and dashed arrows indicate they are between two nodes at least one of which is an unobserved variable.

The indirect mechanism (by way of local prices) is likely to be dominant if farmers sell their crops locally, and if local and international markets are sufficiently integrated (i.e. θ is close to 1). The local presence of multinational companies, for whom international prices matter most and which may buy a significant part of the production, may also represent an important driver of the transmission from international prices to local prices. Furthermore, trade barriers (trade costs, tariffs, etc.), supply chain

Trade flow analyses and trade accounting methods are also limited by their lack of spatial explicitness, leading to imprecise links between consumption patterns and socio-environmental impacts in production regions (Godar et al., 2015).

[6] Because they rely on the recognition of spatial patterns, these methods cannot be used to link the production of – nor demand for – commodities to small-scale deforestation, which may also be related, whether directly or indirectly, to demand in international markets.

frictions, and high shares of local demand may translate into a weak correlation between international and local prices. This is discussed in Section 5.2 where we use a sub-sample of locations in Africa to study the correlation between local and international crop prices. It is found that the correlation is quite high (between 0.82 and 0.98), suggesting that crop markets are relatively integrated.

A direct mechanism is much less likely to exist. Indeed, it is difficult to think of a mechanism that would support the existence of a direct effect. A surge in international prices can push multinational firms to buy local crop production which in turn leads to deforestation. Export-oriented multinational agricultural firms likely play a role in integrating international and local crop markets, rather than there being a direct transmission mechanism.[7]

In order to estimate how local crop prices affect local deforestation, several difficulties had to be overcome. First, in contrast to both international crop prices and deforestation, we do not observe harmonized local crop prices. Second, local crop prices influence decisions to convert forest to agricultural land (γ) and vice versa. Our strategy is therefore to estimate a reduced-form equation for the effect of international crop prices on deforestation, which will provide us with $E(\hat{\beta}) = \beta + \theta\gamma$. If the direct effect of international prices on deforestation is zero, as we believe, then $E(\hat{\beta}) = \theta\gamma$. Finally, if local markets are sufficiently integrated (θ sufficiently close to 1), the strategy provides a good estimate of the effect of local crop prices on deforestation ($E(\hat{\beta})$ close to γ).

Local factors. We claim that land managers are heterogeneously exposed to crop price movements, depending on the extent to which local land is suited to producing these commodities. In other words, fluctuations in the international price of, say, rice primarily affects areas suitable for growing rice and the decision of local land managers to deforest. Differences across locations in the intensity of exposure to specific commodity price movements may generate different deforestation patterns. Although our methodology relates primarily to local crop-specific agronomic suitability to deforestation, other local factors may also play a role. For example, and as suggested in the literature (Ferreira, 2004; Souza-Rodrigues, 2019; Abman and Lundberg, 2020), we expect openness to international trade to magnify the role played by crop prices. In areas naturally more open to trade, such as those closer to seaports, land managers are likely to be more responsive to variations in international commodity prices. Furthermore, local institutional quality and the capacity of states to enforce property rights may also affect the sensitivity of deforestation to crop prices (Angelsen, 1999). Indeed, under open access regimes, for instance, rational farmers should theoretically rush to exploit land and cut forest more quickly (Chichilnisky, 1994; Ferreira, 2004). The impact of the formalization of land rights and land tenure on forest loss has been demonstrated in several cases: a land registration program in Benin (Wren-Lewis et al., 2020); a land titling program in the Brazilian Amazon (Probst et al., 2020); and customary tenure systems in Cameroon (Ordway et al., 2017). Using local-level proxies for trade openness and state capacity, we study how these characteristics affect the link between international crop prices and deforestation in Section 4.2.

[7] Indeed, before these companies even begin crop expansion, they benefit from arbitrage opportunities if the markets are not perfectly integrated. Thus, if the local price is lower than the international price, they will take advantage of the arbitrage opportunity by buying local production (thus increasing local prices) and if the local price is higher than the international price, they will benefit in selling crops locally (thus decreasing local prices). Although we cannot completely exclude a direct effect of international crop prices on local deforestation, it is likely that $\beta = 0$.

3 Data and Empirical Strategy

3.1 Data

We consider a full set of grid cells for the tropics, i.e. the area between the Tropic of Cancer at 23°26' N and the Tropic of Capricorn at 23°26' S, divided into sub-national units of 0.5×0.5 degrees latitude and longitude (approximately 55×55 kilometers at the equator). The unit of observation in our dataset is a cell-year; that is, we estimate how increases in crop prices affect deforestation in a given cell during a given year, within the period 2001-2018.

Deforestation. We use the tree cover loss data from Hansen et al. (2013), which is based on Landsat data. They define tree cover loss as a stand-replacement disturbance or the complete removal of tree cover canopy at the pixel scale.[8] The original data contain an estimation of the annual tree cover loss for the period 2001-2018 (Online Appendix, hereafter OA, Section OA1.1), relative to the 2000 forest cover, for pixels at a spatial resolution of 1 arc-second (around 30 meters). For the baseline estimates, we consider a 1 arc-second pixel as being a forest when the forest cover in year 2000 is greater than 25%, as in other global studies using the same data (Heino et al., 2015; Potapov et al., 2008; Hansen et al., 2010). In the sensitivity analysis, we use a 50% canopy threshold (Section OA2.6). For each of these thresholds, we count the number of pixels defined as deforested within each 0.5×0.5 degrees cell-year. For our baseline measure of deforestation, we consider only cells with more than 5000 pixels of cover in 2000 (i.e. more than 0.125% of the cell's area). Figure OA.1 shows the accumulated deforestation for each pixel during the sample period.

Crop Price Index. We make use of information on global crop prices and agronomic suitability in order to construct our price index. The index is based on information for 15 crops traded on international markets and for which data on both annual global prices and agronomic suitability are available: bananas, barley, cocoa, coconuts, coffee, cotton, maize, palm oil, rice, sorghum, soybeans, sugar, tea, tobacco and wheat. Global crop prices (base 100 in 2000) are obtained from the World Bank Commodity Dataset (World Bank Group, 2020). Data on time-invariant agronomic suitability are obtained from the Global Agro-Ecological Zones (FAO, Fischer et al. (2012)).[9] Agronomic suitability is defined as the percentage of the maximum yield that can be attained in each grid cell. For each cell, we compute the cell-specific *relative* suitability of the crop (α_c^i) by dividing the suitability of the crop (S_c^i) by the sum of the suitability of all the crops as follows:

$$\alpha_c^i = \frac{S_c^i}{\sum_{j=1}^{15} S_c^j}, \tag{1}$$

[8]Note that our data methodology does not, however, capture forest degradation, which has been shown to be surpassing deforestation in the Brazilian Amazon (Matricardi et al., 2020), and affects 10% of tropical moist forests (Vancutsem et al., 2021).

[9]GAEZ, FAO data, available at http://www.fao.org/nr/gaez/about-data-portal/en/

For each cell c and year t, we then compute our price index of crops based on the cell-specific relative suitability of each crop i.

$$\text{Price}_{c,t} = \sum_{i=1}^{15} \alpha_c^i \times P_t^i, \tag{2}$$

where P_t^i is the average worldwide price of crop i in year t.

Figure OA.4 and OA.5 and Table OA.2 present various summary statistics and list the different sources of identifying variations in the price index. Several patterns can be observed in this data: First, there are striking cross-cell differences in the average price index variation over the 2001-2018 period (Figure OA.4). Second, for all crops, there is a substantial variation in price over time, including the two recent spikes related to the 2007-2008 and 2011-2012 global food price crises (Figure OA.5). Third, price correlations between crops are highly heterogeneous, though positive overall, ranging from 4.3% between sugar and palm oil to 96% between sorghum and maize (Table OA.2). Fourth, the share of the total variance of suitability due to within-country variation for each crop is substantial (Table OA.1), ranging from 50% for tobacco to 74% for coconuts. Overall, variations in $\text{Price}_{c,t}$ are substantial even after conditioning on country and year fixed effects, as will be done in our baseline methodology.

Final Sample. The final sample covers the period 2001-2018 and is composed of the 12,288 cells for which agronomic suitability data is available and forest cover is sufficient in 2000, i.e. above 0.125% of the pixels in the cell when the canopy threshold is larger than 25% of the cover. The dataset is therefore a balanced panel of 221,184 observations. Table OA.3 reports summary statistics for the main variables, including initial forest cover, deforestation and the price index $\text{Price}_{c,t}$.

3.2 Empirical strategy

We consider three alternative models. In Model 1, we estimate the impact of the log of the crop price index (ln $\text{Price}_{c,t}$) on the inverse hyperbolic sine transformation of the number of deforested pixels ($\text{Deforest}_{c,t}$) in cell c in year t,[10] while controlling for cell and for country × year fixed effects (η_c and $\nu_{country,t}$, respectively):

$$\text{Deforest}_{c,t} = \beta \ln \text{Price}_{c,t} + \eta_c + \nu_{country,t} + \varepsilon_{c,t}, \tag{3}$$

where $\varepsilon_{c,t}$ is the error term. Standard errors are clustered by cell in the baseline estimation, and in our sensitivity analysis we allow for spatially correlated errors within a larger radius. The inclusion of cell fixed effects controls for any time-invariant cell characteristics that may correlate with both the average deforestation rates and crop prices (such as geography, topography and soil characteristics). The inclusion of country × year fixed effects ($\nu_{country,t}$) accounts for any time-variant country characteristics, such as global trends in overall crop prices, nationwide shocks or policy changes that may trigger or impede deforestation. Since deforestation is bounded by the initial forest cover, we allow the effect of price ($\ln \text{Price}_{c,t}$) to vary across deciles of forest cover throughout the analysis (Model 2). We also allow it

[10]This transformation is frequently used since it approximates the natural logarithm while allowing for zero-valued observations in the estimation (Burbidge et al., 1988; MacKinnon and Magee, 1990; Pence, 2006).

to vary across countries (Model 3) when looking at the effect of cell characteristics. We estimate the models using an Ordinary Least Square (OLS) estimator in the baseline estimations and a Poisson Pseudo Maximum Likelihood (PPML) estimator in the sensitivity exercises. Finally, in order to study the role of local characteristics we estimate equation (3) augmented with interaction terms between $\ln \text{Price}_{c,t}$ and cell-specific proxies of trade openness, development or state capacity (Section 4.2).

Identifying assumptions. In Section 5.1, we explore the sensitivity of the results to our various methodological choices, i.e. estimators, definitions of deforestation, and lagged prices, and across sub-samples of data, i.e. regions, outliers, etc. Perhaps more importantly, we carry out a number of exercises in support of our causal interpretation of the results.

Up to this point, we have interpreted β as an estimate of the impact of international price variation on deforestation (and under additional assumptions, as an estimate of the impact of local price variation; see Section 2). This interpretation would fail if local prices are affected by deforestation and impact international prices as well, or if omitted variables that are cell-specific and vary over time affect both deforestation and world prices. We show that the results are unlikely to be driven by reverse causality, whereby local prices affect world prices, by removing countries that account for a non-negligible share of world production, which leaves the results unchanged (Table OA.11 and OA.12). In addition, in our sensitivity exercises we also control for local weather shocks, which may affect both deforestation and local prices (Table OA.18).

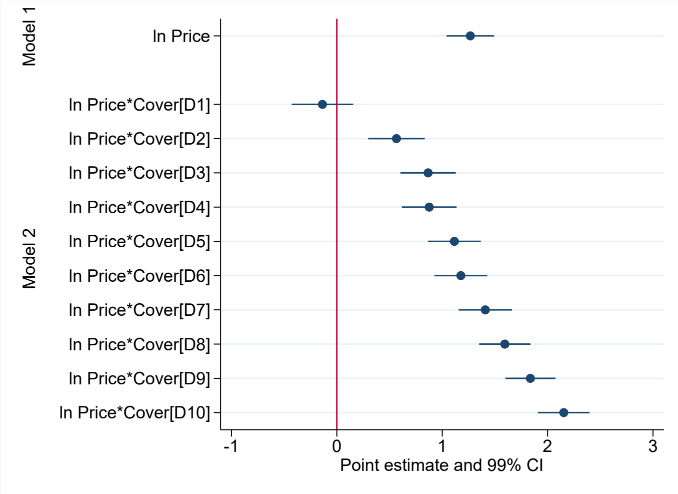
The price index is created using suitability shares and international crop prices and we estimate the effect of variations in this index on deforestation at the cell-year level. Our empirical strategy can therefore be described as a shift-share ("Bartik") reduced-form approach. Moreover, we have a very large number of cells (12,288) and a large number of price shocks (15 crops x 18 years = 270) in the sample. Following Goldsmith-Pinkham et al. (2020), the consistency of our estimator relies on the *exogeneity of the suitability shares to changes in deforestation within cells.* Though not directly testable, this is likely to be a plausible assumption. Forest cover (which conditions changes in deforestation) may correlate with *absolute* suitability (S_c^i) since tropical forest grows on fertile soil. However, our methodology does not consider average suitability, but rather *relative* suitability in specific crops (α_c^i), which are arguably exogenous to deforestation variation. In Section 5.1, we carry out a series of robustness exercises that also support our causal interpretation.

4 Results

4.1 Crop prices and deforestation in the tropics

The baseline results are represented graphically in Figure 2, and the full estimation results are available in Table OA.4. We find that the cell-specific crop price index is positively and significantly correlated with deforestation ($\hat{\beta} = 1.27$, se $= 0.09$). The effect is sizable: a 10% increase in the price index leads to a 12.7% [$\pm$1.7pp] increase in deforestation (Figure 2, Model 1). As the potential for deforestation mechanically depends on the proportion of forest cover at the beginning of the period (Figure OA.2 presents forest cover in 2000), we allow the effect of crop prices to vary across deciles of cell-specific forest cover in 2000 (Figure 2, Model 2). For the first decile of cover, the point estimate is not significantly different from 0; it then triples from the second to tenth decile.[11]

Figure 2: Baseline effects of crop prices on deforestation



Note: Figure 2 presents point estimates and confidence intervals for the effect of the crop price index on deforestation. Model 1 is the baseline estimate of the effect while Model 2 allows the effect of crops on deforestation to differ across deciles of forest cover as of 2000. Horizontal lines represent 95% confidence intervals. See Section 3 and Section OA2.1 for further details.

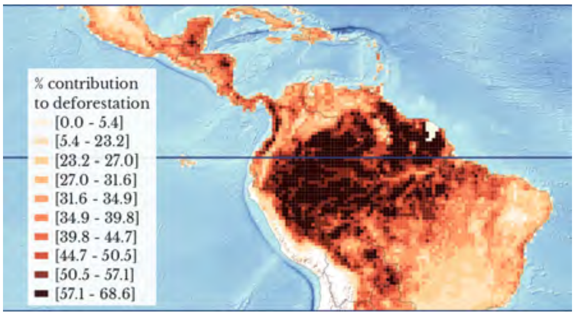
From 2001 to 2018, the crop price index increased on average by more than 40% while the prices of specific leading crops, such as maize, rice, palm oil and soybeans, increased by between 45% and 85%. To get a sense of the role of the rise in crop prices on deforestation, we use the results presented in Figure 2, Model 2 to estimate the total contribution of crop price increases to deforestation during this period.[12] We find that the rise in crop prices was responsible for 35% of predicted global forest loss. Using the PPML estimator rather than OLS leads to similar results (Figure OA.11). In comparison, Harding et al. (2021) find that a 56% increase in commodity prices led to a 19% increase in deforestation in Brazil over the period 2004–2013.

Figure 3 shows the spatial heterogeneity across cells of the contribution of the crop price index variations to deforestation during the sample period. Differences across space are driven by (i) heterogeneous crop-specific suitability, and hence heterogeneous variations in global crop prices (Figure OA.4); and (ii) the cell's initial forest cover (Figure OA.2). A visual inspection reveals that the contribution of the increase in international crop prices to deforestation has been the strongest in the three main tropical moist forest biomes: the Amazon, Southeast Asia and to a lesser extent West and Central Africa. Interestingly, we find

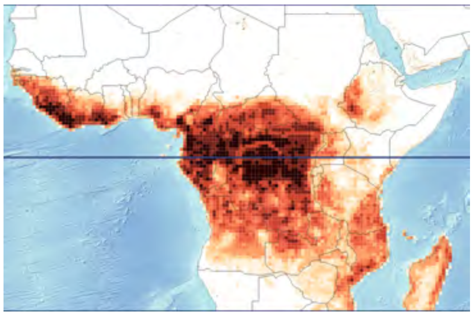
[11] This result is not an artifact of the model specification. Though forest loss is bounded above by the decile of forest cover for each decile bin, in practice these bounds are never reached. To show this, we compute, for each grid cell, the number of deforested pixels over the period and over the initial forest cover of the cell using a canopy threshold of 25% (see Figure OA.3 in Section OA1.4).

[12] Our precise methodology is meant to compute the average contribution of crop price variation over all cells. For each cell, we proceed as follows. We first use the estimates from Model 2 (Figure 2) to compute the predicted level of deforestation, using observed prices (the benchmark). We then compute a counterfactual level of deforestation, using the same estimates but assuming that prices are fixed at their 2001 level. Third, we compute for each cell the contribution of price variation as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

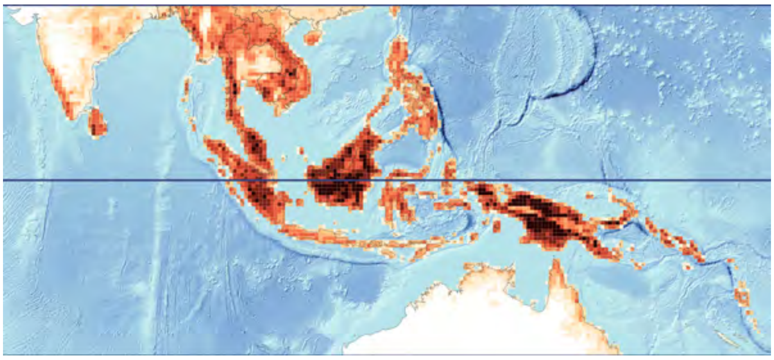
Figure 3: Contribution of crop prices to deforestation, 2001-2018



(a) Americas



(b) Africa



(c) Asia and Oceania

Note: The figure displays the contribution of crop price increases to deforestation. Quantification is based on the estimation results of Model 2 (see Section 3). We first compute the predicted level of deforestation using observed prices (the benchmark). We then compute a counterfactual level of deforestation assuming prices are fixed at their 2001 level. Finally, we sum these predictions by cell over the period and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

that all tropical forests are subject to land pressure stemming from shocks to the prices of internationally traded commodities. Our results validate recent evidence indicating that although cropland expansion in sub-Saharan Africa is still dominated by production for domestic markets, there is a growing influence of global markets on land use in the region (Ordway et al., 2017).

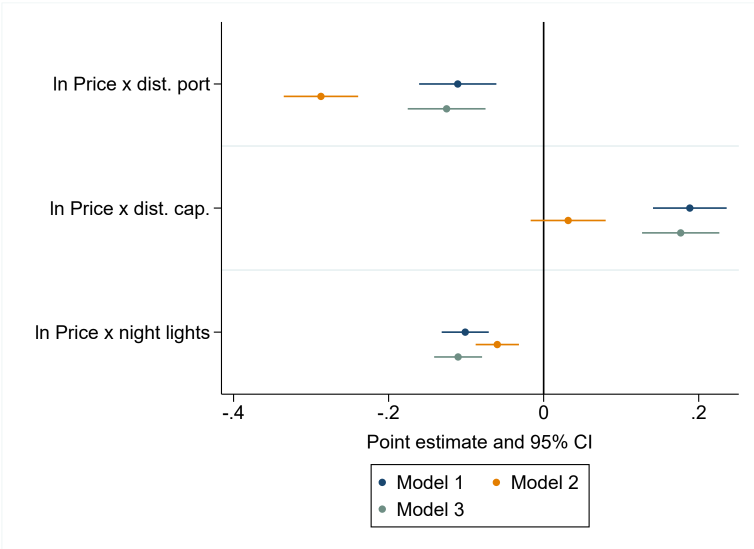
4.2 Trade costs and other local characteristics

As discussed in Section 2, local characteristics may either dampen or exacerbate the contribution of crop price increases to deforestation. We consider two magnifying factors.[13] The first is international trade, such that land managers in areas more open to trade are likely to be more impacted by changes in international prices. To measure the cell-specific exposure to international trade, we use information on the distance from the cell's centroid to the closest major seaport as a proxy for transportation costs (Souza-Rodrigues, 2019). The second factor we consider is state capacity, or local institutional quality. We expect the effect of international crop prices on deforestation to be magnified in areas where the

[13]In Section OA2.5, we also consider heterogeneity at the country-level and include national differences in institutional quality, interacted with our crop price index. The coefficient estimates for these additional variables vary depending on the specification we consider. We discuss these results in Section OA2.5.

capacity of the state to enforce property rights is weaker. To measure institutional quality at the local level, we use the distance between the cell's centroid and the country's capital (Buhaug, 2010).[14] Rule of law, property rights protection and more generally institutional quality are expected to be weaker in places located farther away from the capital (Michalopoulos and Papaioannou, 2014). We also consider a measure of nighttime luminosity in 2000 (i.e. at the beginning of the sample period, in order to avoid reverse causality concerns) as a proxy for local economic development (Henderson et al., 2012; Bruederle and Hodler, 2018). State capacity and institutional quality are also expected to be stronger in wealthier areas. All cell-specific variables have been standardized to make coefficients comparable.

Figure 4: Cell-level characteristics



Note: The figure displays the point estimates and confidence interval of the effect of the interaction between cell-specific characteristics and our price index. The effect of crop price on deforestation is not reported here. Model 1 uses the baseline specification, augmented with interaction terms between the price index and (standardized) cell-characteristic variables (see Section 3 and Table OA.5). Model 2 allows the effect of crop price on deforestation to vary across the deciles of the initial forest cover distribution. Model 3 controls for a full set of interaction terms between country dummies and the price index.

We consider each of these factors by interacting the cell-specific characteristics with our price index in the baseline models. The standardized estimates of the interaction terms are plotted in Figure 4 (the full estimates are available in Table OA.5). Figure 4 considers three models: Models 1 and 2, as in Figure 2; and Model 3, which allows for heterogeneous effects of the price index across countries. In the latter model, we purge the estimates of the interaction terms of their country-wide component (such as differences in country size), in order to focus solely on within-country variation in cell characteristics.

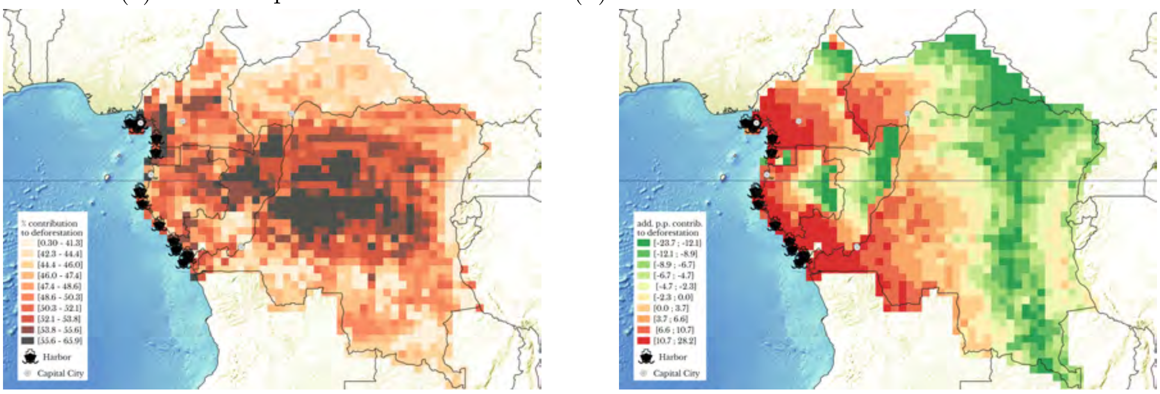
Three findings arise from this analysis. First, we find that the positive effect of crop price increases on deforestation is significantly stronger in cells that are close to a seaport, suggesting that openness to international trade exacerbates the effect of crop price increases on deforestation. Second, and although the significance of the estimate varies, the results point to more extensive commodity-driven deforestation

[14]While there is evidence, especially for African countries, that the power of the State diminishes outside the capital (Michalopoulos and Papaioannou, 2014), measuring local state capacity is nonetheless challenging. Among the potential proxies (such as mountainous terrain (Hendrix, 2011) or road density (Buhaug, 2006)), distance to the capital (Buhaug, 2010) is the most suitable for our purposes since it is the most exogenous and is less related to international trade.

in cells that are more distant from the capital city – i.e. locations with weaker state capacity. Finally, the effect of crop prices on deforestation is smaller in locations that are more economically developed. On average across specifications, distance to a port has the strongest effect. This provides support for the key role of access and exposure to international trade. The effect of trade costs and economic development hardly varied in our sensitivity checks, the effect of local state capacity, as measured by distance to the capital city, is less robust (see Section OA2.6).

Figure 5: Focus on the Congo Basin

(a) Baseline quantification (b) Additional contribution of cell-level characteristics



Note: Figure (a) shows the contribution of crop price increases to forest loss, with the sample restricted to the Congo Basin. The quantification is based on the estimation results of Model 2 (see Section 3). We first compute the predicted level of deforestation using observed prices (the benchmark). We then compute a counterfactual level of deforestation assuming fixed prices at their 2001 level. Finally, we sum these predictions by cell over the period and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual prediction, divided by the counterfactual. Figure (b) shows the difference in p.p. between Figure (a) and the sample quantification based on a specification where interaction terms between prices and cell characteristics are included (dist. port, dist cap. and light lights in 2000). For readability in brown and white, Figure b is reproduced with grey scale in Appendix Figure OA.6.

To illustrate these results, we focus on the Congo Basin, a major tropical moist forest biome spanning several countries. We first repeat the quantification exercise presented in Figure 3, restricting the sample to the countries of the Congo Basin. The results are shown in Figure 5.a, which displays for each cell the contribution of crop price increases to predicted deforestation during the sample period, as well as the location of major seaports and capital cities in each country. Second, we repeat this quantification exercise but use the specification that includes interactions with cell characteristics (Model 2 of Figure 4). Figure 5.b plots the difference in percentage points between the two quantification exercises. Clearly, being close to a port has the strongest effect on commodity-driven deforestation. However, regions that are remote from the capital city also display significant differences, even though they are less exposed to international trade (such as the border between Cameroon and Central African Republic). A visual inspection of the same exercise for the full set of regions in the tropics delivers the same striking spatial patterns (Figure OA.7).

5 Robustness and Interpretation

5.1 Endogeneity concerns and sensitivity analysis

In Section 3.2, we mentioned the two main threats to our identification strategy. The first, is that international prices may be affected by local prices, which are themselves impacted by deforestation or omitted local weather shocks. In other words, variation in our crop price index may be supply-driven rather then demand-driven, and supply may correlate with deforestation. The second is that the validity of our shift-share approach relies on the exogeneity of the suitability shares to changes in deforestation within cells. In this section, we discuss a number of tests which support a causal interpretation of our results.

Market power. We first show that reverse causality is unlikely to be driving our results, that is, they do not reflect the local conditions of countries with enough market power to influence international prices. Indeed, despite the fine-grained level of our analysis and the fact that we are using potential rather than actual agricultural production, we cannot completely rule out the possibility that deforestation and international commodity prices are simultaneously driven by supply-side shocks in major producing countries. For each country and crop, we compute the average market share of world trade during the sample period, and sequentially omit from the estimations countries belonging to the top 10%, 25% and 50% of our sample in terms of global market share. The results remain largely unchanged when focusing only on small producers, which tends to confirm our demand-side interpretation of the results (Tables OA.11 and OA.12).

Confounding factors. Local weather shocks may affect both crop prices (through their effect on agricultural productivity) and deforestation (because, for example, wildfires are more likely in dry years). We add to our baseline specification the average cell-specific yearly temperature and the yearly total amount of precipitation. The results are largely similar to those of the baseline (Figure OA.18). Second, we control for the cell's *absolute* level of agronomic suitability, which may affect both forest cover (hence the likelihood of deforestation) and crop prices (if cells with a higher absolute suitability are also more suitable for specific crops). If the land unsuitable for most crops in the sample is suitable for a crop that has relatively less positive price shocks (such as, for example, coffee) and also lacks forest cover, this may generate a spurious positive relationship between the price index and deforestation since increases in deforestation would necessarily occur in locations where the crop price index has (relatively) large positive shocks. Though such a correlation would be purely accidental, we can eliminate this concern by explicitly controlling for average cell suitability ($\frac{1}{15}\sum_{j=1}^{15} S_c^j$) interacted with year dummies (to control for common price changes). This has little impact on the estimates; if anything, the baseline coefficient slightly increases (Figure OA.12). Finally, in our baseline estimations we focused on agricultural crops and did not include meat in our price index. This may be a concern since studies have linked beef markets to Brazilian forest loss (Bowman, 2016) and land suitable for beef may also be suitable for crop production. To take beef production into account, we use GAEZ suitability data on alfalfa, pasture and grass together with data on the world price of beef available from the World Bank. The methodology and the results are described in Section OA2.6.9 (Figures

OA.14 and OA.15 and Tables OA.19 and OA.20). The results are similar to those of the baseline estimation.

Additional sensitivity analysis. We carry out seven sensitivity analysis (all the tables and graphs related to the sensitivity analysis are relegated to Section OA2.6). First, using the number of deforested pixels as the dependent variable, we estimate the models using a Poisson Pseudo-Maximum Likelihood (PPML) estimator (columns 3 and 4 in Tables OA.7 and OA.8).[15] Second, we consider a different – and more conservative – canopy threshold (50% instead of 25%) to ensure that 30m pixels contain enough tree cover in 2000 to be considered a forest biome (columns 1 and 2 in Tables OA.7 and OA.8). Third, we use the proportion of deforested pixels within forest cover at the beginning of the period as a dependent variable.[16] The main result remains qualitatively similar (Figure OA.13). Fourth, we ensure that the results are not driven by a small number of extreme observations by excluding observations that are 1, 2 and 3 standard deviations away from the residual mean (Tables OA.9 and OA.10). Fifth, we allow for both spatial and serial correlation, since the processes of deforestation and land conversion make it likely that the error term exhibits both. We therefore perform a non-parametric standard errors estimation (Conley, 1999; Hsiang et al., 2011), allowing for both cross-sectional location-specific serial correlation, as well as spatial correlation within a 500 or 1000 km radius (Tables OA.13 and OA.14). Sixth, we relax the assumption that price changes only have a contemporaneous effect on deforestation, by allowing the impact to be lagged (up to t -2) (Tables OA.15 and OA.16). Finally, we estimate the effect separately for South America, Africa and Asia and again obtain qualitatively similar results. In the case of South America, prices exhibit a stronger average impact on deforestation, but this is largely due to the fact that forest cover is higher on average in South America; for high levels of forest cover, the effect, though still larger in South America, becomes more uniform across regions (Table OA.17).

5.2 Mechanisms and interpretation

International and local prices. As mentioned in Section 2, we believe that transmission from international prices to local prices is the mechanism at play and this is consistent with our results. Indeed, using household-level data, the literature has documented that price indexes similar to the one we use, such as those based on local crop-specific suitability and world prices, correlate positively and significantly with farmers' income. For instance, McGuirk and Burke (2020) find a negative correlation between a similar price index and farmer poverty indexes computed from Afrobarometer data. Berman et al. (2021) provide evidence that variations in international market prices of nutrients or fertilizers are indeed transmitted to local markets in Sub-Saharan Africa. Berman et al. (2020) show a positive correlation with various measures of income from three different datasets: the Demographic and Health Surveys, Afrobarometer and World Bank Living Standard Measurement Study surveys.

To provide further evidence for the link between international and local prices, we make use of the data from Porteous (2019), which provides information on local prices for 230 markets across 42 countries and

[15]Since the dependant variable in the deforestation equation is a transformed variable (inverse hyperbolic sine), the quantification of deforested areas includes an error term that is not white noise. For this reason, we replicate our maps using the PPML model (Section OA2.4).

[16]Note that this strategy has the drawback of attributing large weights to cells with very little forest cover.

four different crops (maize, rice, sorghum and wheat). The estimates indicate that the average local prices of crops are clearly correlated with international prices (with the unconditional coefficient of correlation ranging from 0.82 to 0.98). Regressing local prices on world prices, while controlling for market and crop fixed effects, we find that a one-percent increase in the world price is associated with a 0.66 percent increase in the local price (Figure OA.16 and Table OA.21). The magnitude of the effect is similar across crops, except for wheat whose coefficient is close to 1. Although the data only cover a small part of our tropical sample, this suggests that our main result is indeed driven by the response of land managers to local prices.

International demand and trade. Throughout we have interpreted changes in international commodity prices as being demand-driven, which alleviate endogeneity problems associated with supply effects. This also has broader implications, namely that the manipulation of demand, such as changing individual preferences and consumption behavior, can have a direct impact on deforestation. This interpretation of the results in favor of demand effects is reinforced by the fact that we obtain qualitatively similar results when considering commodity imports rather than agricultural prices. To show this, we use changes in the aggregate import demand of trading partners as identification variations.

More specifically, we consider a cell c that is producing crop k exported by country i in which it is located, to country j. We first characterize the importance of export of good k from country i to country j during the period 1990-2000: by defining $\gamma_{ijk} = \frac{X_{ijk}}{X_{ik}}$ as the share of total exports of good k by country i to country j within the total export of country i in good k. We then compute the importance of good k to country j by defining M_{jkt} as the value of country j *total* imports of good k during year t. Finally, we define α_c^k as the relative suitability of crop k in cell c. With these three components, we can compute the following demand index:

$$M_{c,t} = \sum_k \sum_j \alpha_c^k \gamma_{ijk} M_{jkt} \tag{4}$$

Variations in $M_{c,t}$ over time are driven by changes in the total imports of the crops that the cell c is suited to produce by the trading partners of country i. The data to compute these trade shares is taken from FAO-Stats. Though this variable is less straightforward to interpret than prices, it is also more directly demand-driven, since its variation depends solely on the imports of agricultural commodities by trading partners.

The results are qualitatively similar to those obtained using commodity prices (Table 1). Although the effect of price changes and variation in foreign imports cannot be directly compared, the impact of an increase in the trade index on deforestation is substantial: a 10% increase in foreign demand generates a 7% increase in deforestation.

Table 1: Alternative shock: imports in trading partners

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 1	Model 2
Estimator	OLS			
ln $M_{c,t}$	0.703^{a}		0.678^{a}	
	(0.059)		(0.058)	
× Cover[D1]		-0.208^{a}		-0.230^{a}
		(0.071)		(0.071)
× Cover[D2]		0.250^{a}		0.230^{a}
		(0.069)		(0.069)
× Cover[D3]		0.377^{a}		0.359^{a}
		(0.068)		(0.069)
× Cover[D4]		0.425^{a}		0.413^{a}
		(0.068)		(0.068)
× Cover[D5]		0.596^{a}		0.594^{a}
		(0.065)		(0.065)
× Cover[D6]		0.621^{a}		0.614^{a}
		(0.064)		(0.065)
× Cover[D7]		0.704^{a}		0.700^{a}
		(0.064)		(0.064)
× Cover[D8]		0.823^{a}		0.848^{a}
		(0.061)		(0.062)
× Cover[D9]		1.008^{a}		1.038^{a}
		(0.061)		(0.062)
× Cover[D10]		1.209^{a}		1.240^{a}
		(0.063)		(0.064)
ln $M_{c,t}$ × dist. port.			-0.046^{a}	-0.159^{a}
			(0.017)	(0.016)
ln $M_{c,t}$ × dist. cap.			0.155^{a}	0.053^{a}
			(0.013)	(0.014)
ln $M_{c,t}$ × night lights in 2000			-0.051^{a}	-0.030^{a}
			(0.010)	(0.009)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	166392	166392	166392	166392

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors are clustered by cell in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell. Cover[x] are bins for deciles of forest cover in 2000. ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

6 Concluding Remarks

Crop prices are found to be a significant factor explaining deforestation in the tropics at the local level, thus confirming the key role of market forces in deforestation (Pendrill et al., 2019). We present robust statistical evidence that the leading agricultural commodities traded daily in international markets are responsible for a large proportion of global deforestation. As the demand for these products increases, new arable land is needed. It therefore follows that a natural way to arrest deforestation can be found on the demand side: if consumers' demand for agricultural products can be reduced, crop prices will stabilize and deforestation will likely slow. Although our results point to the role of crop price variation in the recent deforestation, additional evidence is needed to better understand the mechanisms and transmission channels from shocks in the global agricultural commodities market to local land use decisions. These channels likely involve various types of actors and potentially different timing across continents and may be highly specific in some countries that are specialized in the exportation of certain types of commodities. A database of harmonized local crop price at the global level would be instrumental in studying this heterogeneity.

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Online Appendix – Not for publication

OA1 Data and descriptive statistics

OA1.1 Tree cover and deforestation

Information on tree cover for the year 2000 is available at a resolution of 1 arc-second (around 30m×30m). The tree cover is defined by Hansen et al. (2013) as canopy closure for all vegetation taller than 5m in height. We consider two thresholds to consider a pixel as a forest: a canopy cover threshold of 25 and 50% of a pixel in year 2000. The main results define forest pixel as having at least 25% of forest cover, while robustness checks were run for a threshold of 50% (Section OA2.6). Hansen et al. (2013) estimate tree cover loss annually over the 2001-2018 period (version 1.6), defined as a stand-replacement disturbance, or a change from a forest to non-forest state. The data provides a year of tree cover loss for every pixel with more than 1% of forest cover (vegetation taller than 5m height) in 2000 that is estimated to endure a loss of more than 50% of the 2000 forest cover between 2001 and 2018. We consider that the whole pixel (30x30m) tree cover was reduced to zero when losses occur. Forest degradation, for example selective removals from within forested stands that do not lead to a non-forest state, was not included in the change characterization. Moreover, the data does not allow to distinguish quality of the canopy and select every vegetation higher than 5m, potentially leading to consider secondary forest loss as deforestation.

OA1.2 Suitability

A crucial information to define our cell-specific price crop index is the crop-specific agronomic suitability of a cell. The FAO provides for the suitability for 45 crops at a resolution of 5 arc minute (FAO's global agroecological zones, GAEZ). These data are constructed from models that use location characteristics, such as climate information (rainfall and temperature, for instance) and soil characteristics. This information is then combined with crops' characteristics (in terms of growing requirements) to generate a global GIS raster of the suitability for each of the 45 crops. Constrained by the availability of international price data, our final sample encompasses 15 crops.

OA1.3 Other data

Throughout the manuscript we make use of different datasets. First, we use information on nighttime lights in 2000 aiming to approximate local economic development.[17] Second, we compute the geodesic distances between each centroid grid cell of 0.5×0.5 degree longitude and latitude and the closest port. We use location of ports from *World Port Index* dataset[18] that provides GPS location of ports with a depth larger than 11 meters. Third, we compute the geodesic distance between each centroid grid cells and the

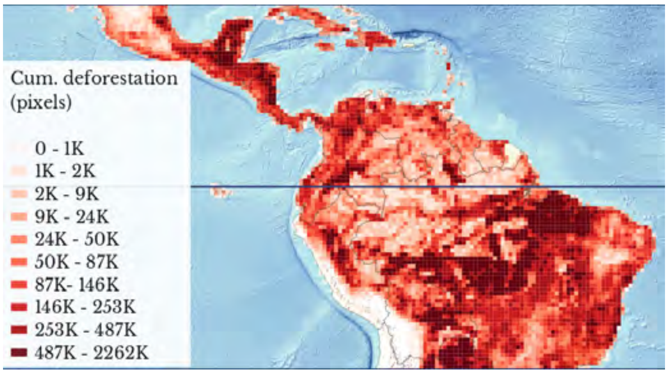
[17] Data from the DMSP-OLS, Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages), as available in PRIO-GRID.

[18] Available at the following link https://msi.nga.mil/Publications/WPI

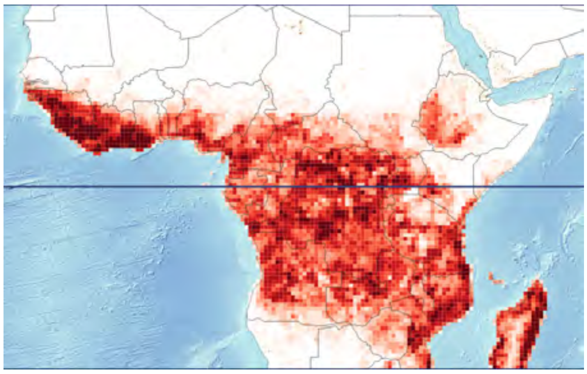
capital city of each country.[19] Fourth, to compute the crop-specific country market share in world trade, we make use of the dataset on exports and imports from the FAO.[20]. Last, we make use of information on rainfall and temperature from the climate research unit from the University of East Anglia.[21]

OA1.4 Forest cover and deforestation: maps and descriptive statistics

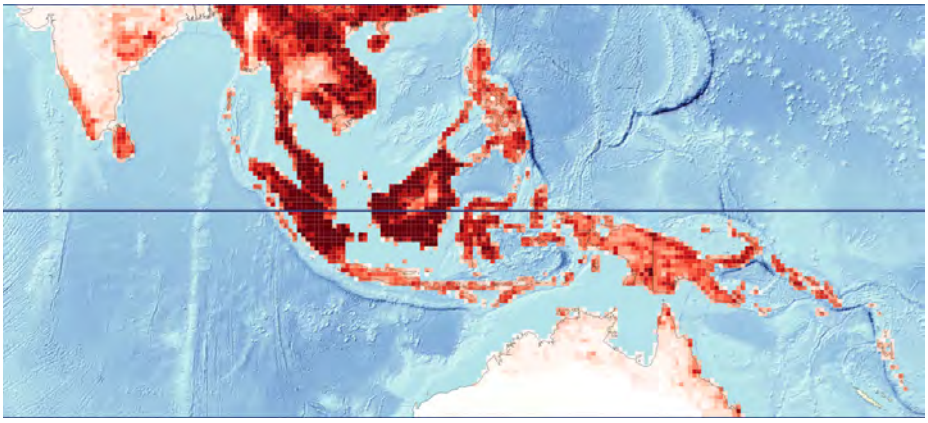
Figure OA.1: Cumulated deforestation, 2001-2018



(a) Americas



(b) Africa



(c) Asia and Oceania

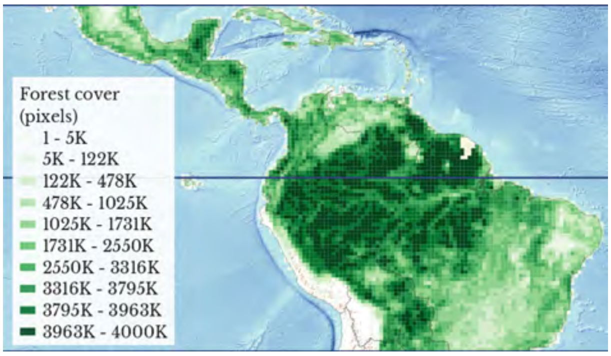
Note: The figure displays accumulated deforestation, in number of pixels (max. total of land pixel in a cell is 4000K), forest defined by a 25% threshold of canopy cover over 1 arc second pixels. Source: Hansen et al. (2013).

[19] We use the distance to the capital city at the beginning of the period, as in a very small number of cases the capital city has changed during the period.

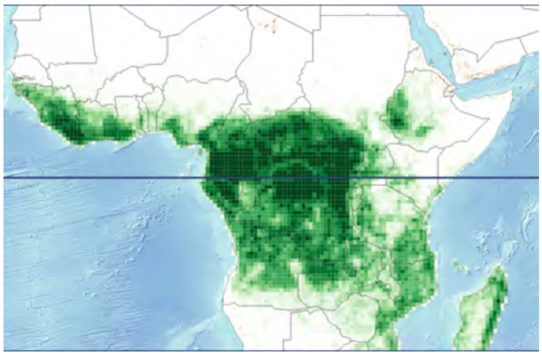
[20] Faostat data site http://www.fao.org/faostat/en

[21] Available at https://crudata.uea.ac.uk/cru/data/hrg/

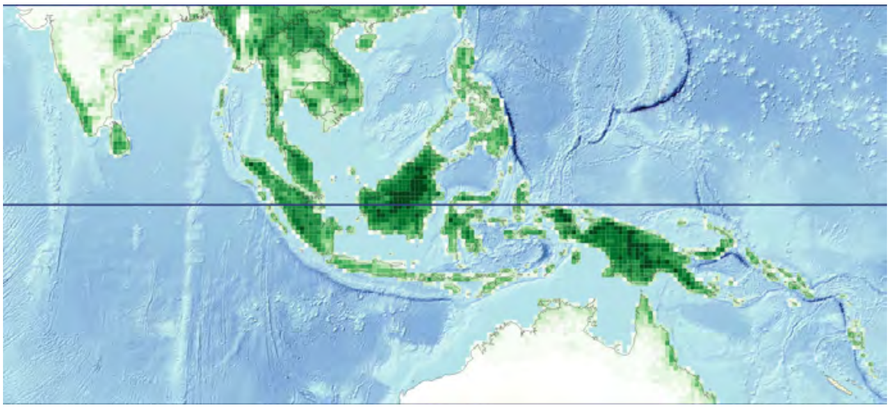
Figure OA.2: Forest cover in 2000



(a) Americas



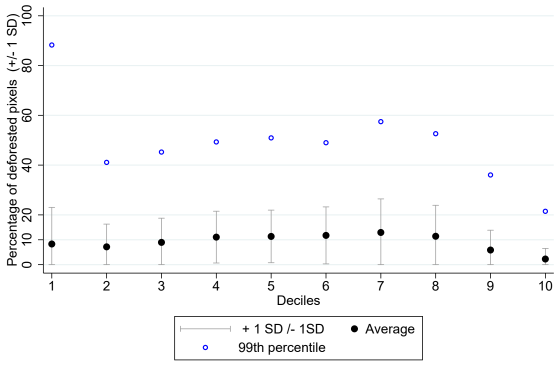
(b) Africa



(c) Asia and Oceania

Note: The figure displays the number of pixels covered by forest in year 2000, using a 25% canopy cover threshold. The maximum total of land pixels per cell is 4000K.

Figure OA.3: Percentage of deforested pixels by cell cover decile



Source: The figure represents the number of deforested pixels over the period over the initial forest cover of the cell, by groups of cells defined based on deciles of initial forest cover. Authors' computation from Hansen et al. (2013), using a canopy threshold of 25%.

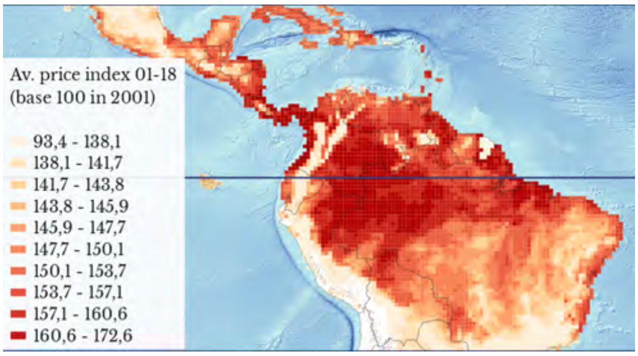
Table OA.1: Suitability within-country variance

Crop	Within Country share	Crop	Within Country share	Crop	Within Country share
Banana	0.61	Cotton	0.58	Sugar	0.69
Barley	0.64	Maize	0.62	Soybean	0.57
Cocoa	0.64	Oil Palm	0.66	Tea	0.70
Coconut	0.74	Rice	0.71	Tobacco	0.50
Coffee	0.64	Sorghum	0.51	Wheat	0.63

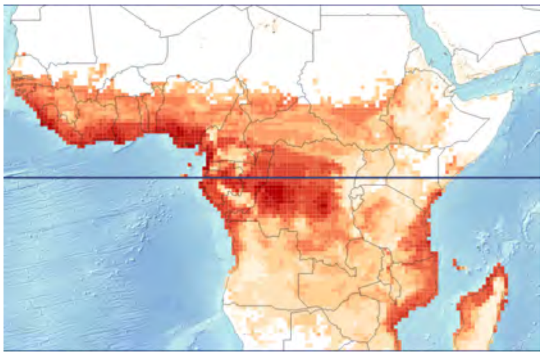
The table displays the share of variance of average cell suitability within country in total variance. Source: Authors' computation from GAEZ data.

OA1.5 International prices: descriptive statistics

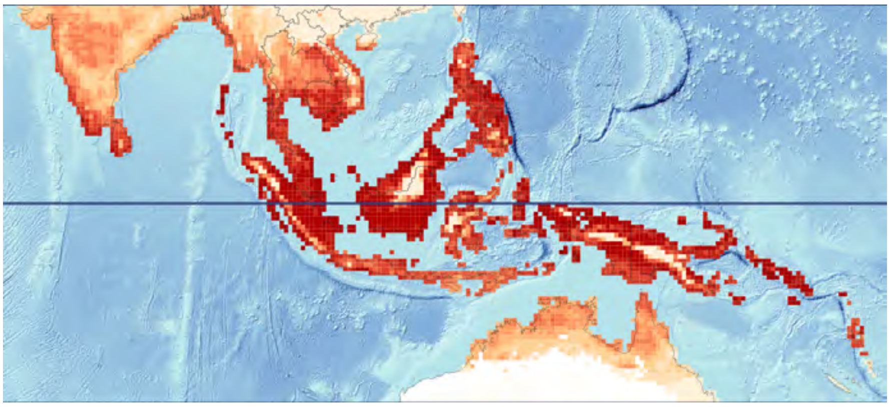
Figure OA.4: Average price index variation, 2001-2018



(a) Americas



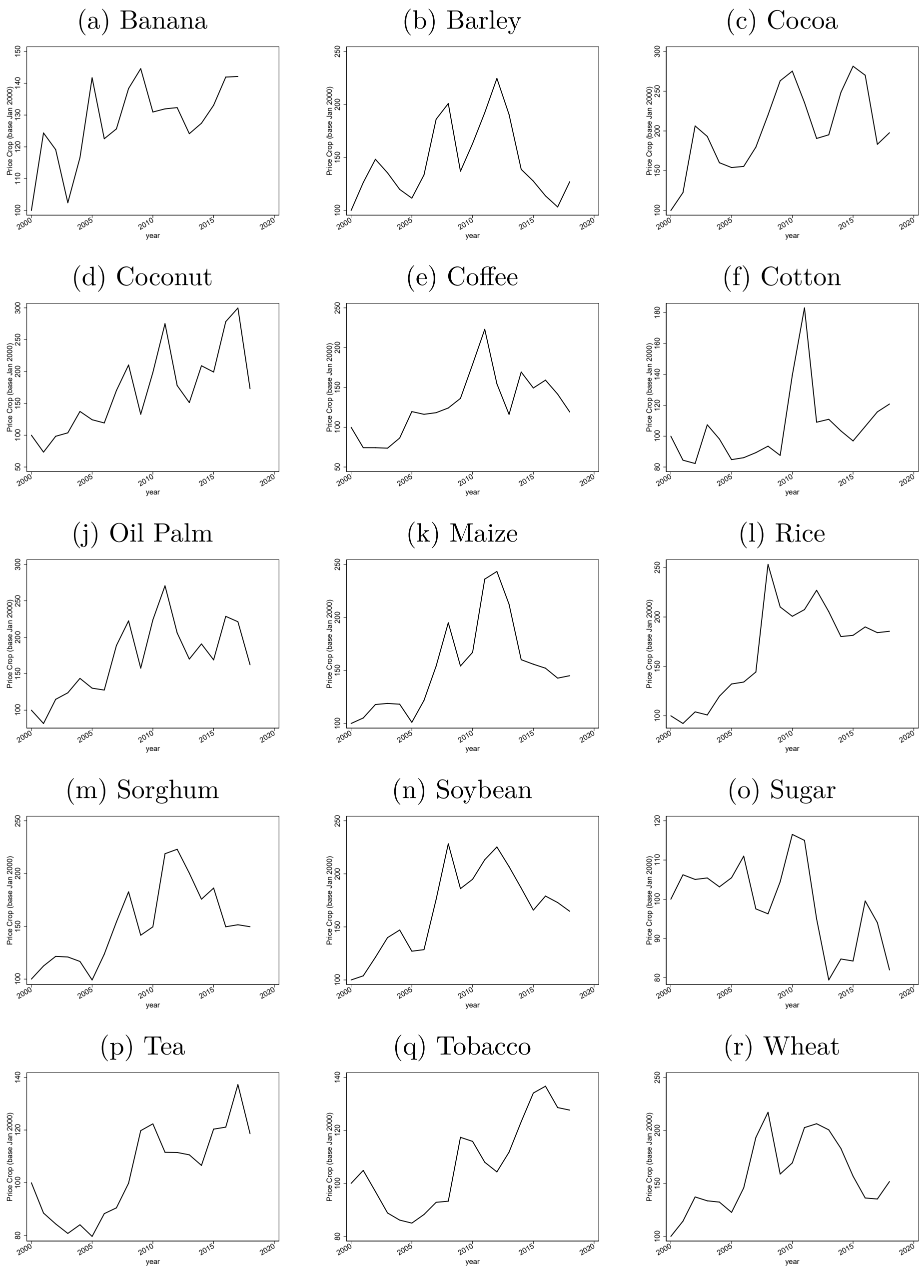
(b) Africa



(c) Asia and Oceania

Note: The table displays the average value of the crop price index over the 2001-2018 period, taking 2001 as a base year.

Figure OA.5: Crop price series



Source: World Bank.

Table OA.2: Crop prices correlation matrix

	banana	barley	cocoa	coconut	coffee	cotton	maize	oilpalm	rice	sorghum	soybean	sugar	tea	tobacco	wheat
banana	1														
barley	0.137	1													
cocoa	0.528	0.231	1												
coconut	0.592	0.154	0.569	1											
coffee	0.552	0.329	0.633	0.783	1										
cotton	0.0802	0.304	0.336	0.593	0.720	1									
maize	0.371	0.839	0.470	0.549	0.677	0.583	1								
oilpalm	0.576	0.485	0.639	0.914	0.852	0.679	0.767	1							
rice	0.681	0.574	0.641	0.676	0.708	0.413	0.831	0.813	1						
sorghum	0.373	0.754	0.526	0.602	0.682	0.536	0.960	0.748	0.804	1					
soybean	0.533	0.736	0.627	0.663	0.684	0.487	0.916	0.861	0.935	0.878	1				
sugar	-0.0820	-0.0348	-0.107	-0.166	0.0465	0.182	-0.205	-0.0425	-0.293	-0.371	-0.249	1			
tea	0.550	0.0283	0.572	0.731	0.652	0.465	0.475	0.640	0.690	0.525	0.552	-0.332	1		
tobacco	0.474	-0.185	0.615	0.612	0.512	0.297	0.257	0.433	0.464	0.389	0.325	-0.469	0.874	1	
wheat	0.345	0.900	0.465	0.427	0.542	0.368	0.894	0.691	0.782	0.870	0.900	-0.241	0.262	0.0693	1

Source: World Bank and authors' computation.

OA1.6 Summary statistics

Table OA.3 displays the summary statistics of all variables used in the paper.

Table OA.3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Forest cover in 2000 (forest: > =25%)	2160762.943	1468356.427	5002	4000000	221184
Forest cover in 2000 (forest: > =50%)	1733182.742	1517453.892	0	4000000	221184
Deforestation (pixel share, forest: > =25%)	0.005	0.01	0	0.43	221184
Deforestation (pixel share, forest: > =50%)	0.008	0.023	0	1	220122
Deforestation (pixel count, forest: > =25%)	10553.688	22859.436	0	749160	221184
Deforestation (pixel count, forest: > =50%)	9074.951	21442.323	0	746363	221184
Inverse hyperbolic sine transformation of Deforestation (pixel count, forest: > =25%)	8.028	2.688	0	14.22	221184
Inverse hyperbolic sine transformation of Deforestation (pixel count, forest: > =50%)	7.417	3.141	0	14.216	221184
Price index	66.763	21.041	1.547	215.39	221184
Distance to nearest seaport in km (dist. port)	604.582	436.82	1.811	1893.287	221184
Distance to capital city in km (dist. cap.)	901.101	793.15	1.773	7916.136	221184
Stable nighttime lights in 2000 (night lights)	0.842	2.594	0	44.547	221184

Note: See appendix Sections OA1.1, OA1.2 and OA1.3 for more details.

OA2 Statistical analysis

OA2.1 Baseline estimates

This sub-section contains the two Tables related to the Figures displaying the baseline estimates in the manuscript. Table OA.4 displays the estimates used to construct Figure 2, Model 1 (Column 1) and Model 2 (Column 2). Table OA.5 shows the estimates used in Figure 4. Column (1) provides the estimates of Model 1, that is of specification (3) when we include interaction variables between the price index and cell characteristics (distance to the closest port, distance to the capital city and the intensity of nighttime lights in 2000). In column (2), we provide the estimates of the same specification, but with the price index interacted with a binary variable for each decile of the initial forest cover distribution. Finally, in column (3) we control for a full set of interactions between country dummies and the price index.

Table OA.4: Baseline results

Model	(1) Model 1	(2) Model 2
ln Price	1.267^a (0.088)	
× Cover[D1]		-0.136 (0.113)
× Cover[D2]		0.566^a (0.104)
× Cover[D3]		0.866^a (0.102)
× Cover[D4]		0.877^a (0.101)
× Cover[D5]		1.115^a (0.097)
× Cover[D6]		1.177^a (0.097)
× Cover[D7]		1.409^a (0.098)
× Cover[D8]		1.594^a (0.094)
× Cover[D9]		1.837^a (0.092)
× Cover[D10]		2.153^a (0.095)
Cell FE	Yes	Yes
Country × Year FE	Yes	Yes
Observations	221184	221184
Period	2001-2018	2001-2018
R^2	0.860	0.861

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000.

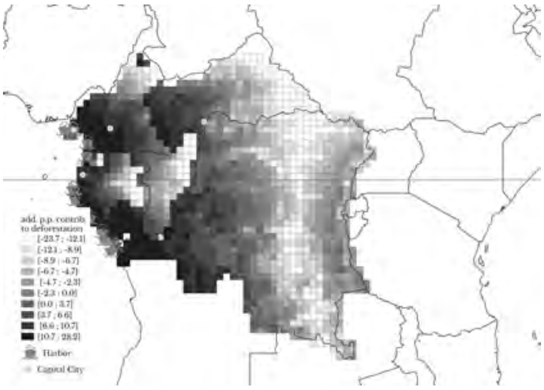
Table OA.5: Baseline results with cell characteristics

	(1) Model 1	(2) Model 2	Model 3
ln Price	1.166^{a}		
	(0.087)		
× ln dist. port	-0.111^{a}	-0.287^{a}	-0.125^{a}
	(0.025)	(0.024)	(0.026)
× ln dist. cap.	0.189^{a}	0.032	0.177^{a}
	(0.024)	(0.025)	(0.025)
× night lights in 2000	-0.101^{a}	-0.060^{a}	-0.110^{a}
	(0.015)	(0.014)	(0.016)
× Cover[D1]		-0.189^{c}	
		(0.113)	
× Cover[D2]		0.512^{a}	
		(0.103)	
× Cover[D3]		0.809^{a}	
		(0.101)	
× Cover[D4]		0.826^{a}	
		(0.100)	
× Cover[D5]		1.077^{a}	
		(0.097)	
× Cover[D6]		1.132^{a}	
		(0.097)	
× Cover[D7]		1.373^{a}	
		(0.097)	
× Cover[D8]		1.625^{a}	
		(0.095)	
× Cover[D9]		1.909^{a}	
		(0.094)	
× Cover[D10]		2.258^{a}	
		(0.098)	
Cell FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Country FE × ln Price	No	No	Yes
Observations	221184	221184	221184
Period	2001-2018	2001-2018	2001-2018

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.2 Focus on the Congo Basin (grey scale)

Figure OA.6: Focus on the Congo Basin: (b) Additional contribution of cell-level characteristics (grey scale)

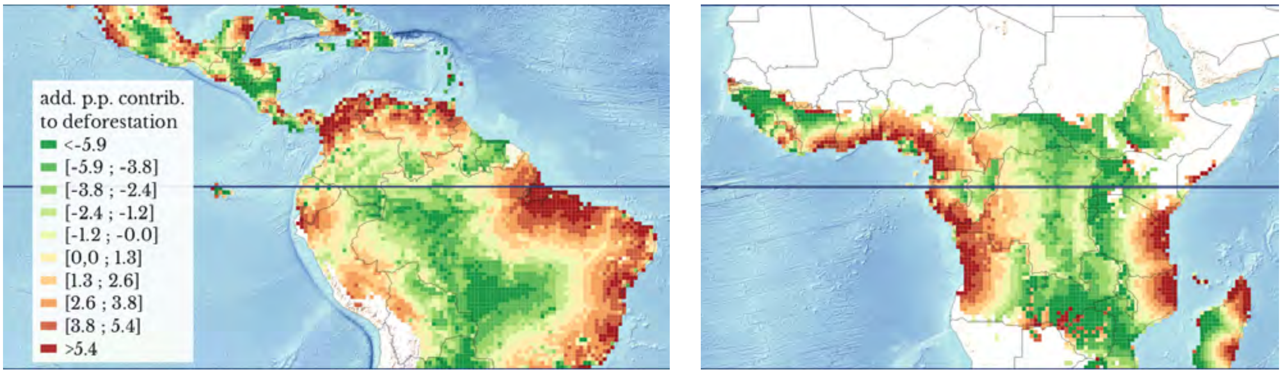


Note: The Figure shows the difference in p.p. between Figure (5.a) and the sample quantification based on a specification where interaction terms between prices and cell characteristics are included (dist. port, dist cap. and light lights in 2000). The quantification is based on the estimation results of Model 2 (see Section 3). We first compute the predicted level of deforestation using observed prices (the benchmark). We then compute a counterfactual level of deforestation assuming fixed prices at their 2001 level. Finally, we sum these predictions by cell over the period and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual prediction, divided by the counterfactual.

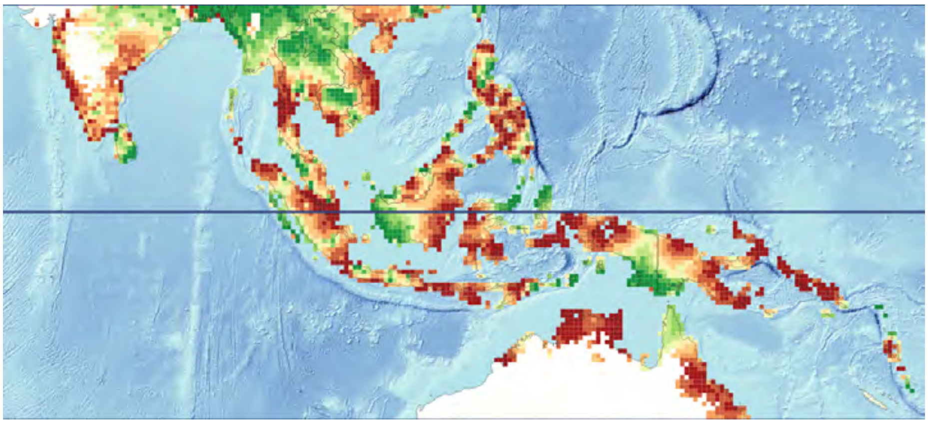
OA2.3 Full quantification with cell-level characteristics

Figure OA.7 provides the same quantification as in Figure 5, but over all the Tropics.

Figure OA.7: Additional contrib. of cell-level characteristics, full Tropics sample



(a) Americas (b) Africa



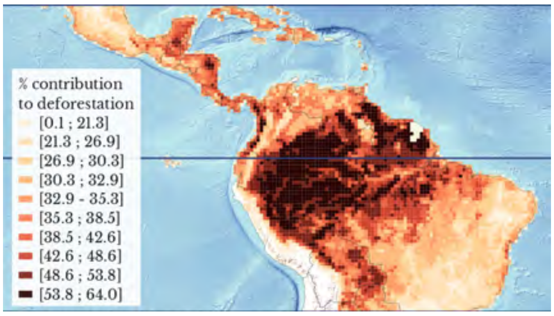
(c) Asia and Oceania

Note: The figure displays the difference (in percentage point) in the contribution of crop prices to deforestation when interacting variables with cell characteristics (Model 2, Figure 3), compared to our baseline (Figure 3). For each model, the quantification is computed in the following way. First, we compute the predicted level of deforestation using observed prices, our benchmark). Then, we compute a counterfactual level of deforestation assuming fixing prices at their 2001 level. Finally, we sum these predictions by cell over the period, and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

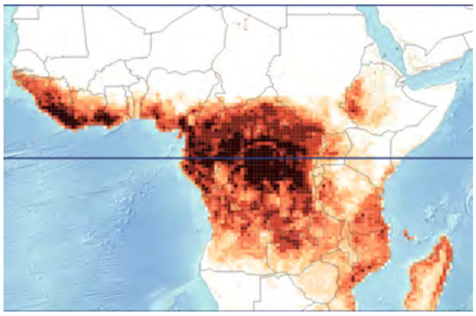
OA2.4 Quantifications, PPML estimator

Figures OA.8 to OA.11 provides the equivalent to Figures 3, 5, OA.6 and OA.7, using a PPML estimator instead of OLS with an Inverse Hyperbolic Sine transformation.

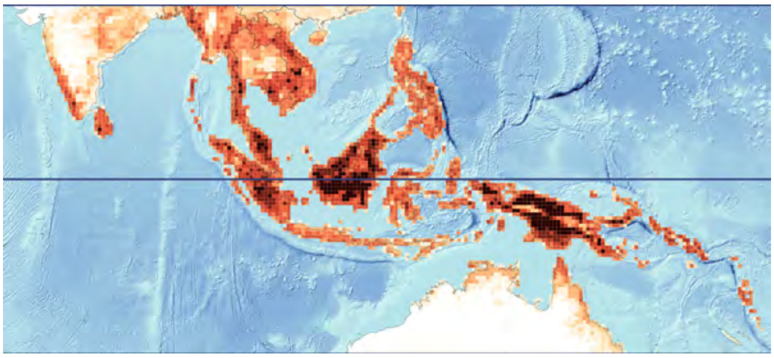
Figure OA.8: Contribution of crop prices increases to deforestation, 2001-2018, PPML



(a) Americas



(b) Africa

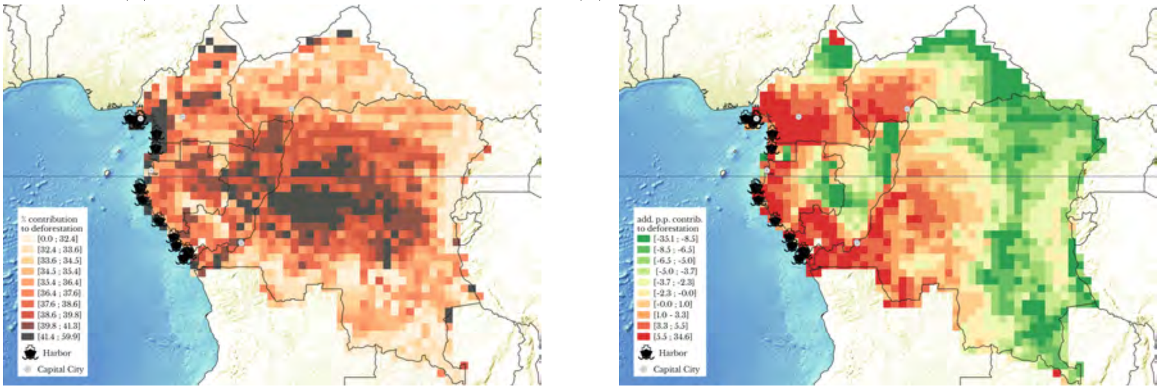


(c) Asia and Oceania

Note: The figure displays the contribution of crop price increases to deforestation, which quantification is based on the estimation results of Model 2 (see Section 3), using a PPML estimator instead of OLS. We first compute the predicted level of deforestation using observed prices, our benchmark). Then we compute a counterfactual level of deforestation assuming fixing prices at their 2001 level. Finally, we sum these predictions by cell over the period, and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

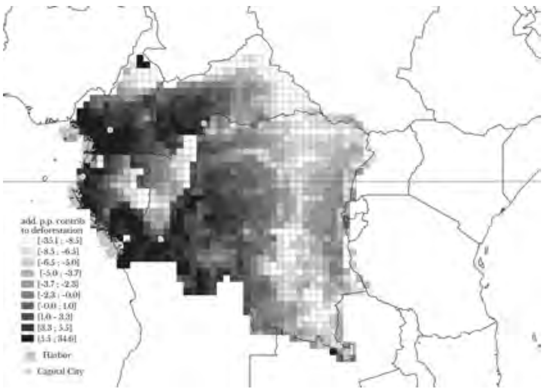
Figure OA.9: Focus on the Congo Basin, PPML estimator

(a) Baseline quantification (b) Additional contribution of cell-level characteristics



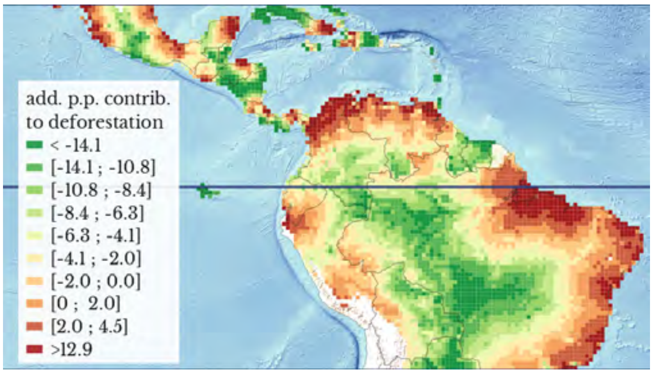
Note: Figure (a) shows the contribution of crop price increases to forest loss, sample restricted to the Congo Basin. The quantification is based on the estimation results of Model 2 (see Section 3), estimated with a PPML estimator instead of OLS. We first compute the predicted level of deforestation using observed prices, our benchmark. Then we compute a counterfactual level of deforestation assuming fixing prices at their 2001 level. Finally, we sum these predictions by cell over the period, and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual. Figure (b) shows the difference in p.p. between Figure (a) and the sample quantification based on a specification where interaction terms between prices and cell characteristics are included, again using a PPML estimator.

Figure OA.10: Focus on the Congo Basin, PPML estimator: (b) Additional contribution of cell-level characteristics (grey scale)

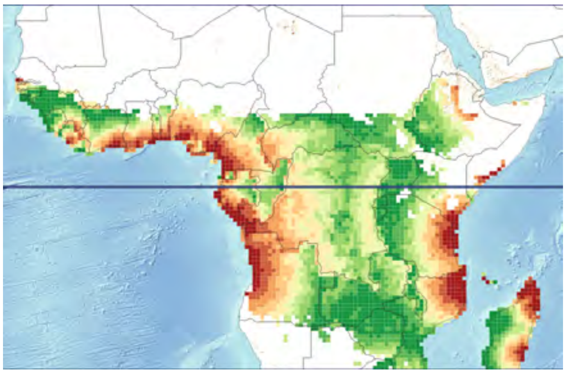


Note: The Figure shows the difference in p.p. between Figure (OA.9.a) and the sample quantification based on a specification where interaction terms between prices and cell characteristics are included, again using a PPML estimator. The quantification is based on the estimation results of Model 2 (see Section 3), estimated with a PPML estimator instead of OLS. We first compute the predicted level of deforestation using observed prices, our benchmark. Then we compute a counterfactual level of deforestation assuming fixing prices at their 2001 level. Finally, we sum these predictions by cell over the period, and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

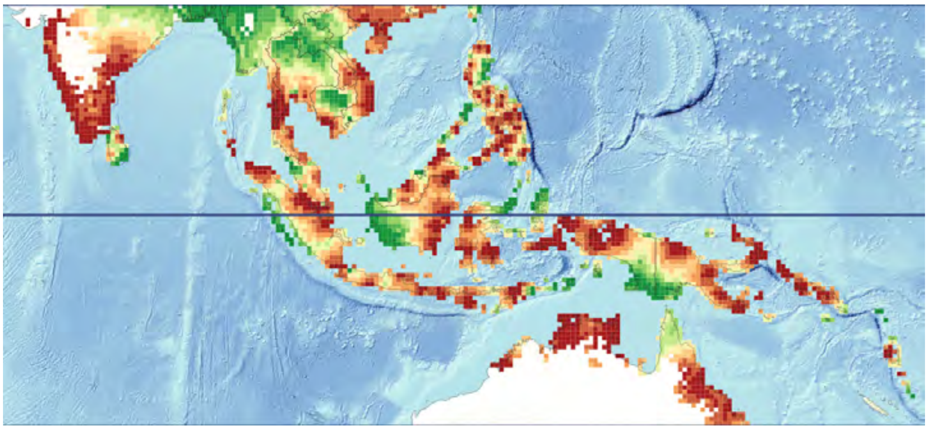
Figure OA.11: Additional contrib. of cell-level characteristics, full Tropics sample, PPML



(a) Americas



(b) Africa



(c) Asia and Oceania

Note: The figure displays the difference (in percentage point) in the contribution of crop prices to deforestation when interacting variables with cell characteristics (Model 2, Figure 3), compared to our baseline (Figure OA.8); these maps use a PPML estimator instead of OLS. For each model, the quantification is computed in the following way. First, we compute the predicted level of deforestation using observed prices, our benchmark). Then, we compute a counterfactual level of deforestation assuming fixing prices at their 2001 level. Finally, we sum these predictions by cell over the period, and compute for each cell the contribution of prices as the difference between the benchmark and the counterfactual predictions, divided by the counterfactual.

OA2.5 Country characteristics

In this section, we use data from the Worldwide Governance Indicators (WBGI) as well as information on GDP per capita and a global measure of institutional quality, the International Country Risk Guide (ICRG) index. We use the value of these variables at the beginning of the period, in 2000, interacted with our price index. We control for continent fixed effects and forest cover, both interacted with our price index.

Table OA.6 displays the results. Several observations can be made. First, though the significance of the effect of distance to capital city varies, the coefficients of cell specific characteristics (distance to port, nighttime luminosity) are quite stable. Second, the significance of the estimates of the country-level institutions variables vary. A high institutional quality (ICRG index) limits the impact of international crop prices on deforestation (columns 1 and 2); GDP per capita does not seem to play a role (columns 2 and 4). In column 4, where all the variables are included, we find that the effect of crop prices is lower in countries with better control of corruption, rule of law and to a lesser extent regulatory quality, but worsens in countries where government effectiveness and accountability are high. Though these are interesting results, interpreting them would require thinking theoretically about how different types of institutions should affect the response of deforestation to crop price variations. Such a theoretical study is beyond the scope of the paper, which is why we chose, in our main results, to control for country characteristics through fixed effects (interacted with prices) rather than directly investigating the impact of country characteristics.

Table OA.6: Baseline results with country characteristics

	(1)	(2)	(3)	(4)
ln Price				
× ln dist. port	-0.269^a	-0.269^a	-0.289^a	-0.289^a
	(0.025)	(0.025)	(0.025)	(0.025)
× ln dist. cap.	0.045^c	0.042	0.020	0.021
	(0.025)	(0.025)	(0.026)	(0.026)
× night lights in 2000	-0.064^a	-0.064^a	-0.070^a	-0.069^a
	(0.014)	(0.014)	(0.015)	(0.015)
× ICRG Index	-4.611^a	-5.477^a		
	(1.222)	(1.328)		
× ln real GDP per cap.		0.327		-0.201
		(0.208)		(0.242)
× Control of corruption (WBGI)			-1.600^b	-1.614^b
			(0.758)	(0.756)
× Voice and accountability (WBGI)			1.928^a	1.948^a
			(0.467)	(0.465)
× Government effectiveness (WBGI)			3.716^a	4.010^a
			(1.072)	(1.067)
× Regulatory Quality (WBGI)			-0.581	-0.731
			(0.598)	(0.596)
× Political Stability (WBGI)			0.795^a	0.758^a
			(0.259)	(0.259)
× Rule of Law (WBGI)			-3.072^a	-2.991^a
			(0.846)	(0.850)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Region FE × ln Price	Yes	Yes	Yes	Yes
Forest cover × ln Price	Yes	Yes	Yes	Yes
Observations	208476	208476	214326	214326

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is our crop price index, defined in equation (2). Forest cover × ln Price is a set of interaction variables, Cover[x] × ln Price, where Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000. All the country level variables are taken at the beginning of the period, in 2000.

OA2.6 Sensitivity analysis

OA2.6.1 Canopy threshold & PPML

Table OA.7: Sensitivity analysis of baseline estimates: canopy threshold & PPML

	(1)	(2)	(3)	(4)
Model	Model 1	Model 2	Model 1	Model 2
Canopy threshold	50%	50%	25%	25%
Estimator	OLS	OLS	PPML	PPML
ln Price	1.351^a		1.377^a	
	(0.088)		(0.117)	
× Cover[D1]		0.080		0.375^b
		(0.113)		(0.167)
× Cover[D2]		0.451^a		0.881^a
		(0.108)		(0.149)
× Cover[D3]		0.761^a		0.877^a
		(0.105)		(0.132)
× Cover[D4]		0.813^a		1.085^a
		(0.104)		(0.134)
× Cover[D5]		1.109^a		1.141^a
		(0.100)		(0.132)
× Cover[D6]		1.193^a		1.093^a
		(0.099)		(0.129)
× Cover[D7]		1.531^a		1.267^a
		(0.099)		(0.126)
× Cover[D8]		1.739^a		1.557^a
		(0.095)		(0.126)
× Cover[D9]		1.990^a		1.768^a
		(0.093)		(0.126)
× Cover[D10]		2.297^a		1.886^a
		(0.096)		(0.148)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	220122	220122	221006	221006

Note: The table shows estimations using the least square estimator in columns (1) and (2) and PPML in columns (3) and (4). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000. With the 50% canopy threshold (columns 1 and 2), the number of observations is reduced compared to the estimates with the 25% canopy threshold as few grid of 0.5 degree do not include any pixels of 30 meters with a 50% canopy cover in 2000.

Table OA.8: Sensitivity analysis of specifications with cell characteristics: canopy threshold & PPML estimator

	(1)	(2)	(3)	(4)
Model	Model 1	Model 2	Model 1	Model 2
Canopy threshold	50%	50%	25%	25%
Estimator	OLS	OLS	PPML	PPML
ln Price	1.248^{a}		1.109^{a}	
	(0.088)		(0.111)	
× ln dist. port	-0.119^{a}	-0.328^{a}	-0.417^{a}	-0.484^{a}
	(0.027)	(0.026)	(0.035)	(0.035)
× ln dist. cap.	0.193^{a}	0.003	0.205^{a}	0.099^{a}
	(0.025)	(0.025)	(0.038)	(0.037)
× night lights in 2000	-0.103^{a}	-0.051^{a}	-0.093^{a}	-0.038^{b}
	(0.017)	(0.015)	(0.018)	(0.017)
× Cover[D1]		0.027		0.110
		(0.112)		(0.164)
× Cover[D2]		0.397^{a}		0.546^{a}
		(0.107)		(0.145)
× Cover[D3]		0.700^{a}		0.511^{a}
		(0.104)		(0.126)
× Cover[D4]		0.760^{a}		0.745^{a}
		(0.103)		(0.128)
× Cover[D5]		1.071^{a}		0.860^{a}
		(0.099)		(0.126)
× Cover[D6]		1.153^{a}		0.788^{a}
		(0.098)		(0.124)
× Cover[D7]		1.506^{a}		0.978^{a}
		(0.098)		(0.119)
× Cover[D8]		1.800^{a}		1.319^{a}
		(0.096)		(0.120)
× Cover[D9]		2.105^{a}		1.575^{a}
		(0.095)		(0.121)
× Cover[D10]		2.455^{a}		1.782^{a}
		(0.099)		(0.143)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	220122	220122	221006	221006

Note: The table shows estimations using the least square estimator in columns (1) and (2) and PPML in columns (3) and (4). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.6.2 Outliers

Table OA.9: Sensitivity analysis of the baseline estimates: dropping outliers

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2
Sample: Excluded outliers	3 σ	2 σ	1 σ	3 σ	2 σ	1 σ
ln Price	1.116^a	0.994^a	0.905^a			
	(0.072)	(0.061)	(0.042)			
$\times$ Cover[D1]				-0.245^a	-0.259^a	-0.430^a
				(0.093)	(0.077)	(0.052)
$\times$ Cover[D2]				0.417^a	0.346^a	0.181^a
				(0.085)	(0.073)	(0.049)
$\times$ Cover[D3]				0.691^a	0.574^a	0.465^a
				(0.083)	(0.070)	(0.048)
$\times$ Cover[D4]				0.728^a	0.617^a	0.419^a
				(0.082)	(0.071)	(0.048)
$\times$ Cover[D5]				0.931^a	0.835^a	0.680^a
				(0.082)	(0.070)	(0.047)
$\times$ Cover[D6]				0.977^a	0.877^a	0.732^a
				(0.082)	(0.071)	(0.048)
$\times$ Cover[D7]				1.207^a	1.095^a	0.920^a
				(0.082)	(0.070)	(0.048)
$\times$ Cover[D8]				1.410^a	1.297^a	1.113^a
				(0.079)	(0.068)	(0.047)
$\times$ Cover[D9]				1.651^a	1.503^a	1.352^a
				(0.078)	(0.067)	(0.046)
$\times$ Cover[D10]				1.987^a	1.854^a	1.628^a
				(0.080)	(0.069)	(0.047)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217908	210305	171382	217913	210312	171342

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000.

Table OA.10: Sensitivity analysis of specifications with cell characteristics: dropping outliers

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2
Sample: Excluded outliers	3 σ	2 σ	1 σ	3 σ	2 σ	1 σ
ln Price	0.995^a	0.888^a	0.802^a			
	(0.082)	(0.071)	(0.048)			
× ln dist. port	-0.264^a	-0.266^a	-0.190^a	-0.676^a	-0.646^a	-0.547^a
	(0.064)	(0.055)	(0.037)	(0.062)	(0.055)	(0.037)
× ln dist. cap.	0.469^a	0.445^a	0.350^a	0.037	0.021	-0.046
	(0.061)	(0.053)	(0.035)	(0.060)	(0.052)	(0.035)
× night lights in 2000	-0.041^a	-0.036^a	-0.030^a	-0.026^a	-0.020^a	-0.017^a
	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)
× Cover[D1]				0.051	0.025	-0.138^b
				(0.100)	(0.085)	(0.057)
× Cover[D2]				0.716^a	0.627^a	0.470^a
				(0.094)	(0.081)	(0.054)
× Cover[D3]				0.991^a	0.852^a	0.754^a
				(0.090)	(0.078)	(0.053)
× Cover[D4]				1.024^a	0.895^a	0.704^a
				(0.090)	(0.078)	(0.053)
× Cover[D5]				1.238^a	1.123^a	0.966^a
				(0.090)	(0.077)	(0.052)
× Cover[D6]				1.276^a	1.161^a	1.020^a
				(0.090)	(0.078)	(0.054)
× Cover[D7]				1.512^a	1.380^a	1.218^a
				(0.090)	(0.078)	(0.054)
× Cover[D8]				1.756^a	1.624^a	1.455^a
				(0.091)	(0.079)	(0.054)
× Cover[D9]				2.030^a	1.864^a	1.713^a
				(0.092)	(0.080)	(0.055)
× Cover[D10]				2.386^a	2.231^a	2.002^a
				(0.096)	(0.083)	(0.057)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217898	210295	171419	217912	210298	171388

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.6.3 Dropping large players

Table OA.11: Sensitivity analysis of the baseline estimates: dropping countries with a large crop market share

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2
Sample: Excluded	Top 10%	Top 25%	Top 50%	Top 10%	Top 25%	Top 50%
ln Price	1.449^a	1.449^a	0.921^a			
	(0.095)	(0.095)	(0.128)			
× Cover[D1]				0.115	0.115	-0.164
				(0.125)	(0.125)	(0.159)
× Cover[D2]				0.709^a	0.709^a	0.288^c
				(0.115)	(0.115)	(0.152)
× Cover[D3]				0.926^a	0.926^a	0.746^a
				(0.112)	(0.112)	(0.147)
× Cover[D4]				0.934^a	0.934^a	0.867^a
				(0.111)	(0.111)	(0.150)
× Cover[D5]				1.178^a	1.178^a	0.966^a
				(0.107)	(0.107)	(0.145)
× Cover[D6]				1.247^a	1.247^a	1.113^a
				(0.107)	(0.107)	(0.146)
× Cover[D7]				1.456^a	1.456^a	1.320^a
				(0.110)	(0.110)	(0.150)
× Cover[D8]				1.692^a	1.692^a	1.470^a
				(0.104)	(0.104)	(0.143)
× Cover[D9]				1.947^a	1.947^a	1.568^a
				(0.101)	(0.101)	(0.139)
× Cover[D10]				2.384^a	2.384^a	1.849^a
				(0.105)	(0.105)	(0.153)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171990	171990	87624	171990	171990	87624

Note: The table shows estimations using the least square estimator. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000. In columns (1) and (4), we dropped the top 10% of the countries with respect to their average market share in our sample's crops post-2000 (top 25% in columns (2) and (5) and top 50% in columns (3) and (6)). The crops considered to compute the market shares are those included in our analysis: banana, barley, cocoa, coconut, coffee, cotton, maize, oil palm, rice, sorghum, soybean, sugar, tea, tobacco, wheat.

Table OA.12: Sensitivity analysis of specifications with cell characteristics: dropping countries with a large crop market share

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2
Sample: Excluded	Top 10%	Top 25%	Top 50%	Top 10%	Top 25%	Top 50%
ln Price	1.449^{a}	1.449^{a}	0.921^{a}			
	(0.095)	(0.095)	(0.128)			
× Cover[D1]				0.115	0.115	-0.164
				(0.125)	(0.125)	(0.159)
× Cover[D2]				0.709^{a}	0.709^{a}	0.288^{c}
				(0.115)	(0.115)	(0.152)
× Cover[D3]				0.926^{a}	0.926^{a}	0.746^{a}
				(0.112)	(0.112)	(0.147)
× Cover[D4]				0.934^{a}	0.934^{a}	0.867^{a}
				(0.111)	(0.111)	(0.150)
× Cover[D5]				1.178^{a}	1.178^{a}	0.966^{a}
				(0.107)	(0.107)	(0.145)
× Cover[D6]				1.247^{a}	1.247^{a}	1.113^{a}
				(0.107)	(0.107)	(0.146)
× Cover[D7]				1.456^{a}	1.456^{a}	1.320^{a}
				(0.110)	(0.110)	(0.150)
× Cover[D8]				1.692^{a}	1.692^{a}	1.470^{a}
				(0.104)	(0.104)	(0.143)
× Cover[D9]				1.947^{a}	1.947^{a}	1.568^{a}
				(0.101)	(0.101)	(0.139)
× Cover[D10]				2.384^{a}	2.384^{a}	1.849^{a}
				(0.105)	(0.105)	(0.153)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171990	171990	87624	171990	171990	87624

Note: The table shows estimations using the least square estimator. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000. In columns (1) and (4), we dropped the top 10% of the countries with respect to their average market share in our sample's crops post-2000 (top 25% in columns (2) and (5) and top 50% in columns (3) and (6)). ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.6.4 Conley standard errors

Table OA.13: Sensitivity analysis of the baseline estimates: Conley's standard errors

	(1)	(2)	(3)	(4)
Model	Model 1	Model 2	Model 1	Model 2
Spatial threshold	500km	500km	1000km	1000km
ln Price	1.267^a		1.267^a	
	(0.307)		(0.372)	
× Cover[D1]		-0.136		-0.136
		(0.319)		(0.371)
× Cover[D2]		0.566^c		0.566^c
		(0.297)		(0.340)
× Cover[D3]		0.866^a		0.866^a
		(0.292)		(0.330)
× Cover[D4]		0.877^a		0.877^a
		(0.292)		(0.329)
× Cover[D5]		1.115^a		1.115^a
		(0.294)		(0.338)
× Cover[D6]		1.177^a		1.177^a
		(0.296)		(0.337)
× Cover[D7]		1.409^a		1.409^a
		(0.304)		(0.347)
× Cover[D8]		1.594^a		1.594^a
		(0.302)		(0.350)
× Cover[D9]		1.837^a		1.837^a
		(0.302)		(0.359)
× Cover[D10]		2.153^a		2.153^a
		(0.318)		(0.372)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	221184	221184	221184	221184

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors allowing for infinite serial correlation and spatial correlation within a 500km or 1000km radius are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000.

Table OA.14: Sensitivity analysis of specifications with cell characteristics: Conley standard errors

	(1)	(2)	(3)	(4)
Model	Model 1	Model 2	Model 1	Model 2
Spatial threshold	500km	500km	1000km	1000km
ln Price	1.220^a		1.220^a	
	(0.310)		(0.369)	
× ln dist. port	-0.293	-0.703^a	-0.293	-0.703^a
	(0.190)	(0.182)	(0.200)	(0.187)
× ln dist. cap.	0.367^b	-0.038	0.367^c	-0.038
	(0.183)	(0.165)	(0.210)	(0.182)
× night lights in 2000	-0.040^a	-0.023^b	-0.040^a	-0.023^b
	(0.010)	(0.009)	(0.010)	(0.010)
ln Price*Cover[D1]		0.210		0.210
		(0.329)		(0.386)
ln Price*Cover[D2]		0.909^a		0.909^b
		(0.311)		(0.357)
ln Price*Cover[D3]		1.204^a		1.204^a
		(0.307)		(0.349)
ln Price*Cover[D4]		1.212^a		1.212^a
		(0.306)		(0.347)
ln Price*Cover[D5]		1.458^a		1.458^a
		(0.309)		(0.357)
ln Price*Cover[D6]		1.520^a		1.520^a
		(0.310)		(0.356)
ln Price*Cover[D7]		1.756^a		1.756^a
		(0.318)		(0.365)
ln Price*Cover[D8]		1.997^a		1.997^a
		(0.318)		(0.370)
ln Price*Cover[D9]		2.276^a		2.276^a
		(0.320)		(0.381)
ln Price*Cover[D10]		2.621^a		2.621^a
		(0.334)		(0.396)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	221184	221184	221184	221184

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.6.5 Lagged effect

Table OA.15: Sensitivity analysis of the baseline estimates: lags

Model	(1) Model 1	(2) Model 1	(3) Model 1	(4) Model 2
ln Price	1.267^a		1.030^a	
	(0.088)		(0.098)	
ln Price: average t to $t-2$		1.915^a		
		(0.154)		
ln Price: $t-1$			0.330^a	
			(0.096)	
ln Price: $t-2$			0.694^a	
			(0.113)	
ln Price: average t to $t-2$ × Cover[D1]				0.253
				(0.176)
ln Price: average t to $t-2$ × Cover[D2]				1.261^a
				(0.165)
ln Price: average t to $t-2$ × Cover[D3]				1.614^a
				(0.163)
ln Price: average t to $t-2$ × Cover[D4]				1.724^a
				(0.164)
ln Price: average t to $t-2$ × Cover[D5]				1.964^a
				(0.159)
ln Price: average t to $t-2$ × Cover[D6]				2.080^a
				(0.159)
ln Price: average t to $t-2$ × Cover[D7]				2.344^a
				(0.162)
ln Price: average t to $t-2$ × Cover[D8]				2.632^a
				(0.158)
ln Price: average t to $t-2$ × Cover[D9]				3.000^a
				(0.158)
ln Price: average t to $t-2$ × Cover[D10]				3.469^a
				(0.162)
Cell FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Observations	221184	196608	196608	196608

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2) and ln Price: average t to $t-2$ is the average price from t to $t-2$.

Table OA.16: Sensitivity analysis of specifications with cell characteristics: lags

Model	(1) Model 1	(2) Model 2
ln Price: average t to $t-2$	1.738^{a}	
	(0.152)	
× ln dist. port	-0.130^{a}	-0.360^{a}
	(0.032)	(0.031)
× ln dist. cap	0.317^{a}	0.098^{a}
	(0.029)	(0.029)
× night lights in 2000	-0.090^{a}	-0.034^{c}
	(0.019)	(0.018)
ln Price: average t to $t-2$ × Cover[D1]		0.154
		(0.174)
ln Price: average t to $t-2$ × Cover[D2]		1.162^{a}
		(0.164)
ln Price: average t to $t-2$ × Cover[D3]		1.512^{a}
		(0.162)
ln Price: average t to $t-2$ × Cover[D4]		1.635^{a}
		(0.162)
ln Price: average t to $t-2$ × Cover[D5]		1.889^{a}
		(0.158)
ln Price: average t to $t-2$ × Cover[D6]		1.992^{a}
		(0.157)
ln Price: average t to $t-2$ × Cover[D7]		2.268^{a}
		(0.160)
ln Price: average t to $t-2$ × Cover[D8]		2.631^{a}
		(0.158)
ln Price: average t to $t-2$ × Cover[D9]		3.039^{a}
		(0.159)
ln Price: average t to $t-2$ × Cover[D10]		3.536^{a}
		(0.164)
Cell FE	Yes	Yes
Country × Year FE	Yes	Yes
Observations	196608	196608

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), ln Price: average t to $t-2$ is the average price from t to $t-2$, ln dist. port is the log of distance from the closest seaport. ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000.

OA2.6.6 Baseline results by continent

Table OA.17: Baseline results by continent

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Continent	Africa		America		Asia	
ln Price	0.393^b		1.839^a		0.569^b	
	(0.190)		(0.110)		(0.228)	
× Cover[D1]		-0.979^a		1.025^a		-0.260
		(0.209)		(0.198)		(0.244)
× Cover[D2]		-0.236		0.906^a		0.523^b
		(0.205)		(0.159)		(0.235)
× Cover[D3]		0.419^b		0.771^a		0.863^a
		(0.208)		(0.135)		(0.244)
× Cover[D4]		0.526^b		0.816^a		0.810^a
		(0.209)		(0.132)		(0.244)
× Cover[D5]		0.724^a		1.083^a		1.030^a
		(0.205)		(0.129)		(0.234)
× Cover[D6]		0.797^a		1.064^a		1.159^a
		(0.208)		(0.129)		(0.233)
× Cover[D7]		1.023^a		1.374^a		1.146^a
		(0.204)		(0.132)		(0.240)
× Cover[D8]		0.979^a		1.671^a		1.420^a
		(0.202)		(0.119)		(0.249)
× Cover[D9]		1.030^a		2.041^a		1.573^a
		(0.206)		(0.116)		(0.237)
× Cover[D10]		1.135^a		2.463^a		1.301^a
		(0.207)		(0.118)		(0.287)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73692	73692	91116	91116	56232	56232

Note: The table shows estimations using the least square estimator with cell and country × year fixed effects. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000.

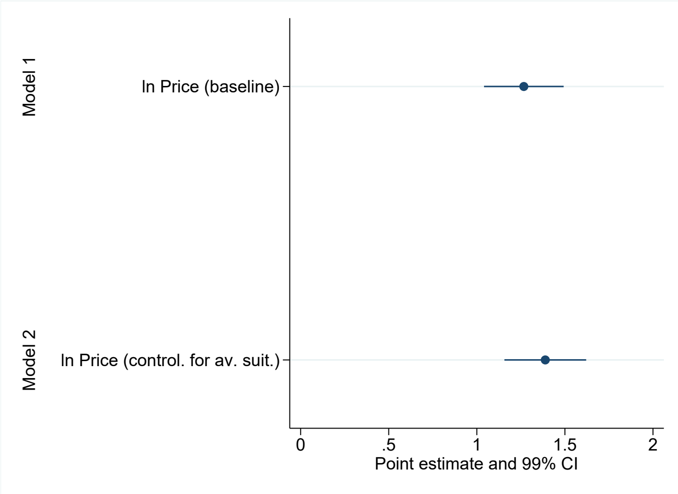
OA2.6.7 Controlling for time-varying covariates

Table OA.18: Controlling for precipitation and temperature

	(1) Model 1	(2) Model 1	(3) Model 2
ln Price	1.267^a	1.237^a	
	(0.088)	(0.087)	
Average temperature		0.237^a	0.224^a
		(0.022)	(0.022)
Average precipitation		-0.000^a	-0.000^a
		(0.000)	(0.000)
ln Price*Cover[D1]			-0.163
			(0.113)
ln Price*Cover[D2]			0.549^a
			(0.104)
ln Price*Cover[D3]			0.853^a
			(0.102)
ln Price*Cover[D4]			0.862^a
			(0.100)
ln Price*Cover[D5]			1.097^a
			(0.097)
ln Price*Cover[D6]			1.152^a
			(0.097)
ln Price*Cover[D7]			1.380^a
			(0.098)
ln Price*Cover[D8]			1.562^a
			(0.094)
ln Price*Cover[D9]			1.800^a
			(0.092)
ln Price*Cover[D10]			2.112^a
			(0.095)
Cell FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Observations	221184	221184	221184

Note: The table shows estimations using the least square estimator with cell and country × year fixed effects. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000. Average temperature and Average precipitation are the yearly average temperature and precipitation of the cell, respectively.

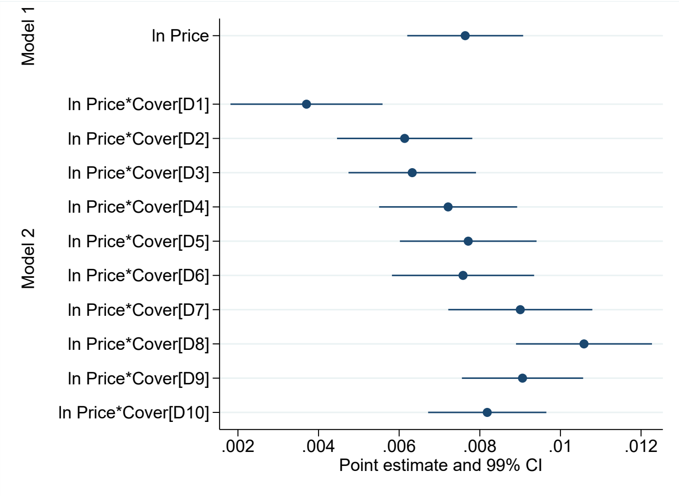
Figure OA.12: Controlling for average suitability



Note: The figure displays the point estimates and confidence intervals for the effect of the crop price index on deforestation. Model 1 is the baseline estimate of the effect while Model 2 controls for average cell suitability interacted with year dummies. Horizontal lines represent 99% confidence intervals.

OA2.6.8 Relative deforestation: percent of 2000 forest cover

Figure OA.13: Relative deforestation: percent of 2000 forest cover



Note: The figure displays the point estimates and confidence intervals for the effect of the crop price index on deforestation. Model 1 is the baseline estimate of the effect while Model 2 allows the effect of crops on the share of deforested pixels (relative to forest cover in 2000) to vary across deciles of forest cover as of 2000. Horizontal lines represent 99% confidence intervals.

OA2.6.9 Considering meat and pasture, rangeland, and grassland

For our baseline price index and baseline estimations, we choose to concentrate on agricultural crops, and do not include meat, because meat production does not rely on land as strongly and systematically as production of agricultural crops. Beef can be produced on or off the grassland. When beef is produced off the grassland, it is fed hay or grain that is transported to the beef production site. Thus, the place where the beef is raised and the place where the grass grows is not always the same. This is a major difference with crop production. In addition, we do not have direct data on "beef suitability" but rather indirect data on the type of soil that can be consumed by beef as food.

With these remarks in mind, we replicate here our estimations with a revised price index that considers beef markets. More precisely, we use GAEZ suitability data for alfalfa, pasture and grass together with data on the world price of beef from the World Bank. We build the modified price index as follows. We first add the suitability of alfalfa, pasture and grass to have a measure of "beef suitability" for each cell c, $S_c^{16} = S_c^{alfalfa} + S_c^{pasture} + S_c^{grass}$. We then compute the relative suitability of each crop $i = 1, ..., 15$ and beef $i = 16$:

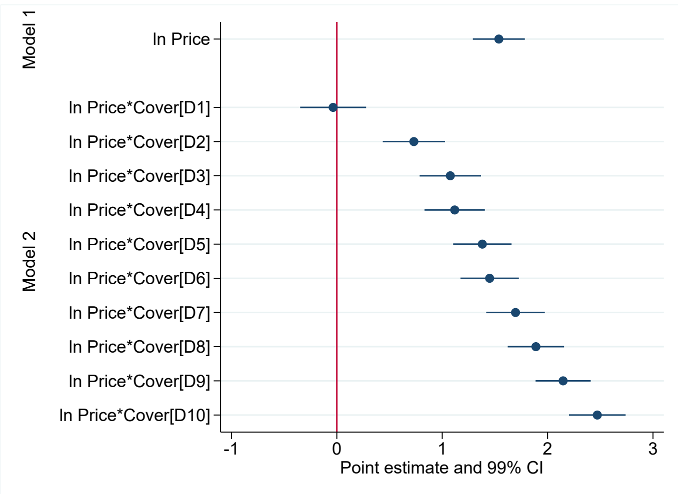
$$\alpha_c^i = \frac{S_c^i}{\sum_{j=1}^{16} S_c^j}. \tag{OA.5}$$

Then, for each cell c and year t, we compute our modified price index of crops and beef based on the cell-specific relative suitability of each crop and beef:

$$\text{Price}_{c,t} = \sum_{i=1}^{16} \alpha_c^i \times P_t^i, \tag{OA.6}$$

Figures OA.14 and OA.15 and Tables OA.19 and OA.20 display the results.

Figure OA.14: Baseline effects of crop prices on deforestation (incl. meat)



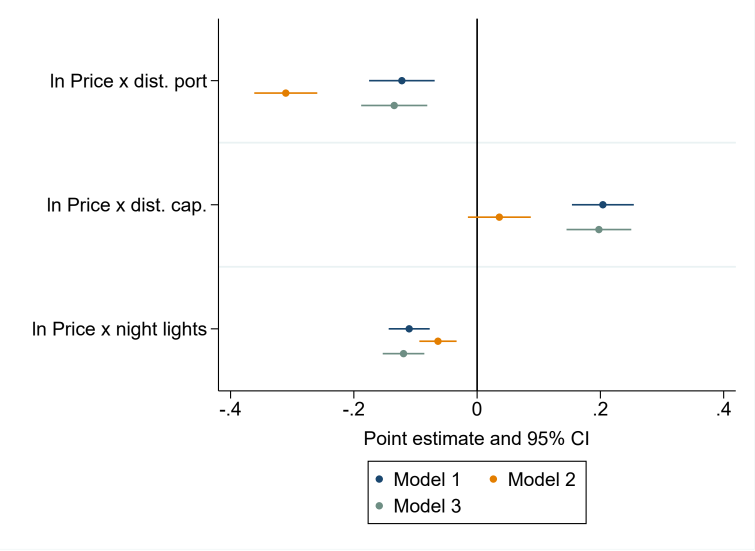
Note: The figure displays the point estimates and confidence intervals for the effect of the crop price index on deforestation. The crop price index includes meat prices, and the relative suitability of alfalfa, pasture and grass used as measure of meat suitability. Model 1 is the baseline estimate of the effect while Model 2 allows the effect to vary across deciles of forest cover as of 2000. Horizontal lines represent 99% confidence intervals.

Table OA.19: Baseline results (incl. meat)

	(1) Model 1	(2) Model 2
ln Price	1.537^a	
	(0.096)	
× Cover[D1]		-0.035
		(0.121)
× Cover[D2]		0.731^a
		(0.115)
× Cover[D3]		1.077^a
		(0.113)
× Cover[D4]		1.118^a
		(0.111)
× Cover[D5]		1.381^a
		(0.107)
× Cover[D6]		1.450^a
		(0.108)
× Cover[D7]		1.696^a
		(0.108)
× Cover[D8]		1.889^a
		(0.104)
× Cover[D9]		2.147^a
		(0.102)
× Cover[D10]		2.472^a
		(0.104)
Cell FE	Yes	Yes
Country × Year FE	Yes	Yes
Observations	221184	221184
Period	2001-2018	2001-2018

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, Ln Price is the log of our crop price index, defined in equation (2) and Cover[x] are bins for deciles of forest cover in 2000. The crop price index includes meat prices, with share of alfalfa, pasture and grass suitability used as measure of meat suitability.

Figure OA.15: Cell-level characteristics (incl. meat)



Note: The figure displays the point estimates and confidence interval of the effect of the interaction between cell-specific characteristics and our price index. The crop price index includes meat prices, and the relative suitability of alfalfa, pasture and grass used as measure of meat suitability. The effect of crop price on deforestation is not reported here. Model 1 uses the baseline specification, augmented with interaction terms between the price index and (standardized) cell-characteristic variables (see Section 3). Model 2 allows the effect of crop price on deforestation to vary across the deciles of the initial forest cover distribution. Model 3 controls for a full set of interaction terms between country dummies and the price index.

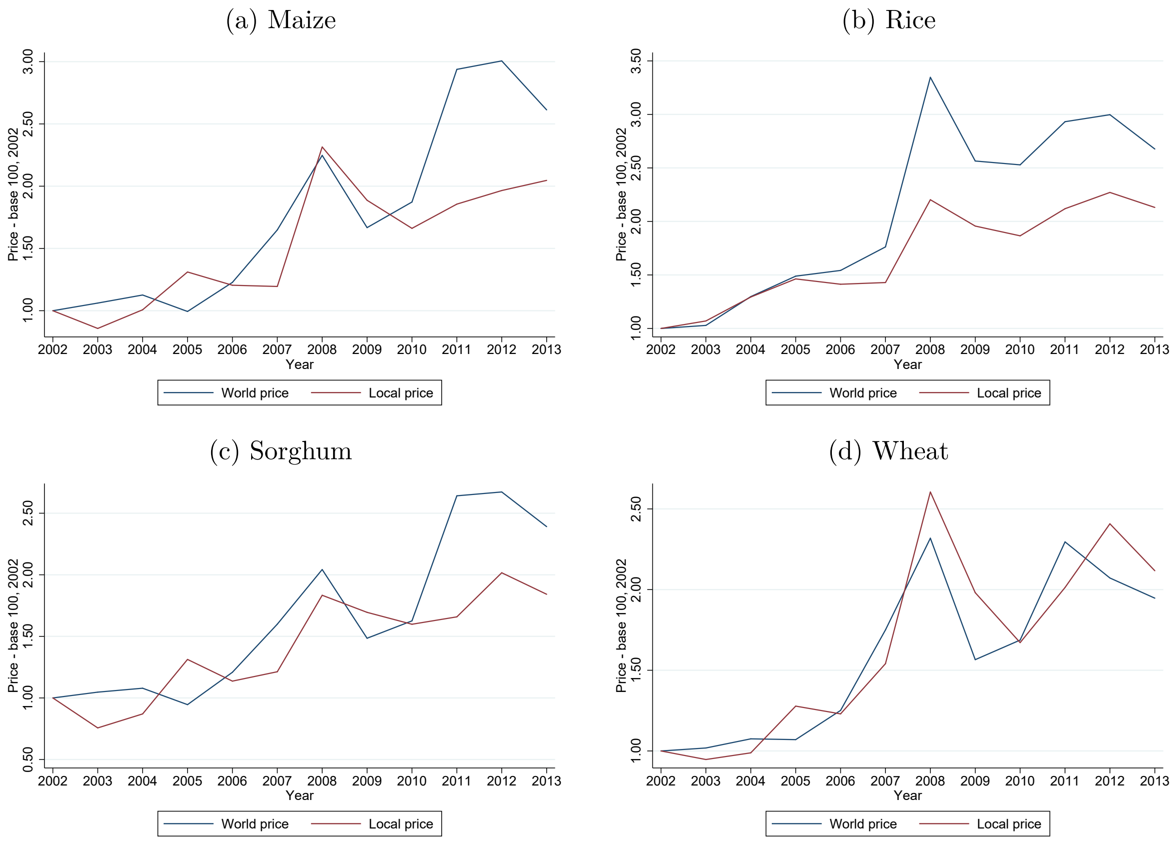
Table OA.20: Baseline results with cell characteristics (incl. meat)

	(1) Model 1	(2) Model 2	Model 3
ln Price	1.406^{a}		
	(0.096)		
× ln dist. port	-0.122^{a}	-0.310^{a}	-0.134^{a}
	(0.027)	(0.026)	(0.027)
× ln dist. cap.	0.204^{a}	0.036	0.198^{a}
	(0.026)	(0.026)	(0.027)
× night lights in 2000	-0.110^{a}	-0.064^{a}	-0.119^{a}
	(0.017)	(0.015)	(0.017)
× Cover[D1]		-0.094	
		(0.121)	
× Cover[D2]		0.671^{a}	
		(0.114)	
× Cover[D3]		1.013^{a}	
		(0.112)	
× Cover[D4]		1.061^{a}	
		(0.110)	
× Cover[D5]		1.337^{a}	
		(0.107)	
× Cover[D6]		1.399^{a}	
		(0.107)	
× Cover[D7]		1.654^{a}	
		(0.107)	
× Cover[D8]		1.919^{a}	
		(0.105)	
× Cover[D9]		2.222^{a}	
		(0.103)	
× Cover[D10]		2.580^{a}	
		(0.108)	
Cell FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Country FE × ln Price	No	No	Yes
Observations	221184	221184	221184
Period	2001-2018	2001-2018	2001-2018

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered at the cell level are in parentheses. The dependent variable is the hyperbolic inverse sine of the number of pixels deforested in the cell, ln Price is the log of our crop price index, defined in equation (2), Cover[x] are bins for deciles of forest cover in 2000, ln dist. port is the log of distance from the closest seaport, ln dist. cap. is the log of the distance from the country's capital city at the beginning of the period and night lights is the average amount of nighttime lights emitted in the cell in 2000. The crop price index includes meat prices, with share of alfalfa, pasture and grass suitability used as measure of meat suitability.

OA2.7 Global and local prices: correlations

Figure OA.16: Local and word prices



Source: Porteous (2019) and World Bank.

Table OA.21: Correlation local prices and world prices

	(1)	(2)	(3)	(4)	(5)
Dep. var.			Local price		
World price	0.659^{a}	0.610^{a}	0.694^{a}	0.689^{a}	0.960^{a}
	(0.023)	(0.032)	(0.026)	(0.036)	(0.074)
Sample (crops included)	All	Maize	Rice	Sorghum	Wheat
Market FE	Yes	Yes	Yes	Yes	Yes
Crop FE	Yes	No	No	No	No
Observations	3292	1403	868	873	145

Note: The table shows estimations using the least square estimator. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Data on local prices are from Porteous (2019). Local price is the log of the local market price. World price is the log of the international price.