Deforestation in the Amazon: A Unified Framework for Estimation and Policy Analysis

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Abstract

Deforestation is a matter of pressing global concern, yet surprisingly little is known about the relative efficacy of various policies designed to combat it. This paper sets out a framework for measuring the cost effectiveness of alternative policies – both command-and-control and incentive-based – in the Brazilian Amazon. First, I estimate the demand for deforestation on private properties, exploiting regional variation in transportation costs as a means of recovering farmers' responses to permanent policies. By rescaling transportation costs using local yields, I am able to value the changes in private values in dollars per hectare. I then use the estimated demand to infer farmers' willingness to deforest under different counterfactual policies, such as payments to avoid deforestation and taxes on land use, along with the corresponding potential farmers' lost surpluses. The results indicate that payment programs and land-use taxes on agricultural land can be highly effective in preserving the rainforest and can also be substantially less expensive than command-and-control policies (approximately ten times less costly). A carbon tax equal to the social cost of carbon could virtually eliminate all agricultural land in the Amazon, given the low agricultural returns and the vast carbon stock found there.

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KEYWORDS: deforestation, land use, carbon tax, Amazon, rainforest, quantile instrumental variables, social cost of carbon.

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1 Introduction

Deforestation is a matter of global concern, not least because of its clear linkage to the pressing issue of climate change. One fifth of greenhouse gas emissions during the 1990s and one tenth during the 2000s have been attributed to deforestation and forest degradation (IPCC (2007, 2013)). Further, reducing deforestation is viewed as a highly cost-effective means of reducing emissions – see, for example, the Stern Review (2007). Absent global coordination, the most likely arena for implementing policy initiatives to combat deforestation is at the national level. In that context, the Brazilian government has been particularly active, both as home to the largest expanse of intact rainforest on the planet, and because of intense deforestation over the past three decades.[1] The main focus of the federal government has been on quantitative (command-and-control) policies limiting land use on private and public land, and while recent efforts to monitor and enforce restrictions applying to new deforestation have yielded some success, the rainforest continues to shrink.

Incentive-based interventions are potentially appealing alternatives to quantitative command-and-control policies. Examples include payment programs, carbon and land use taxes, and emissions trading.[2] In theory, they can achieve any level of protection at the lowest possible cost to society. While eliminating wasteful expenditures is an important objective by itself and can help avoid political strife, less is known in practice about the magnitudes of these costs, and how they compare to quantitative command-and-control policies. At a general level, the accurate measurement of costs of environmental policies is understood to be a challenging problem, as noted by Pizer and Kopp (2005). In a deforestation context, a key obstacle is a lack of clear framework based on credible estimation of the process – often decentralized – that leads to deforestation, which can then be used to generate reasonable quantitative policy prescriptions. This paper aims to fill that gap.

To that end, I develop a unified approach for measuring the cost effectiveness of alternative policies – both command-and-control and incentive-related – in the Brazilian Amazon. The framework is based on a revealed preference approach, uses credible microeconometric estimates, and can be applied to both existing and yet-to-be implemented policies.

A key component of the framework is the demand for deforestation on private properties. This is

[1] The accumulated deforestation in the Brazilian Amazon between 1988 and 2017 was approximately 42.8 million hectares, which is an area larger than the state of California (INPE (2017)).

[2] Payment programs pay suppliers directly to provide environmental services (Pattanayak, Wunder and Ferraro (2010)). REDD+ is the most prominent example: countries with high emissions can pay to protect forests in developing nations and count the storage of carbon in their overall carbon output. It has been negotiated by the United Nations Framework Convention on Climate Change (UNFCCC) since 2005, and it formed part of the Cancun Agreements in December 2010, at COP-16. Environmental taxes are defined as taxes levied on the production of negative externalities – the carbon tax is the most well-known example. When the measurement of the externalities is difficult, payments and taxes can be directed to the adoption of particular land uses.

defined as the function relating the amount of deforested area to the difference between the private value of the agricultural and forested land.[3] It provides farmers' willingness to deforest at different levels of private costs (affected by potential taxes and payments), as well as the corresponding potential surpluses.

To identify demand, I exploit the fact that regional variation in transportation costs can be used to infer the value of agricultural land relative to forested land. To gain some intuition, consider one farm located close to a major port and another that is far away. *Ceteris paribus*, as transportation costs increase, both the values of agricultural and forested land should decrease, yet if the value of the agricultural land is disproportionately affected by transportation costs, its *relative* value should also fall. As a result, one would expect less deforestation in farms located farther away from the port. In this way, variation in transportation costs can be exploited to infer how farmers will respond to changes in private costs. By rescaling the transportation costs using local yields, I am able to value the difference between these two forms of land use in dollars per hectare. The strategy I propose is therefore divided into two steps: first, I estimate the effects of transportation costs on deforestation, and second, I rescale these costs using local yields to recover the demand function.[4]

My focus is on permanent policies and on permanent effects, as opposed to transitional dynamics. Because deforesting is costly, farmers are more likely to respond to persistent changes in private values than to temporary changes. Policy interventions will thus have substantial impacts on deforestation only if they are put into effect for a long period of time. In this vein, exploiting regional variation in transportation costs is appropriate because persistent changes in private values are likely to be captured by differences in transportation costs in a geographical cross-section.[5]

To estimate the model, I combine the Brazilian transportation network of 2006 with the Agricultural Census of 2006, which is the most recent and comprehensive data set available for the agricultural sector in the country. I also supplement the data with detailed spatial information relating to important determinants of land use, such as soil quality, topography, temperature and

[3] The vast majority of the deforested areas in the Amazon are used for agriculture, mostly pasture and cropland (see Section 3).

[4] The impacts of transportation costs are estimated using the instrumental variable quantile regression estimator proposed by Chernozhukov and Hansen (2008); an extensive and detailed discussion of the identification strategy is presented in Subsection 4.2. The use of quantile regressions allows for heterogeneous impacts and is discussed in Sections 2 and 4. As a robustness exercise, I also estimated a semiparametric model using the penalized sieve minimum distance estimator proposed by Chen and Pouzo (2012). The results of the semiparametric model are presented in the Supplemental Material.

[5] See Berry (2011) for a discussion of the importance of distinguishing the short-run and the long-run land-use elasticities for biofuels policies, and Scott (2013) for a fully dynamic model of land-use for the US. Important contributions to the literature that develops empirical land use models include Stavins and Jafee (1990), Stavins (1999), Pfaff (1999), and Mason and Platinga (2013), among others. The relationship of the current analysis to the literature is discussed in Section 2.

rainfall. The estimates show significant negative impacts of transportation costs on deforestation, as might be expected.

After estimating the model, I investigate the effects of three policy interventions: (a) payments for ecological services (PES); (b) taxes on agricultural land; and (c) quantitative limits on the deforestation allowed on private properties. Large-scale payment programs and land-use taxes have not yet been adopted in the Brazilian Amazon. Instead, the federal government has relied on quantitative limits. By law, landowners in the Amazon are obligated to keep 80 percent of their properties as native forest (the '80 percent rule'). Yet, there is ample evidence that this rule has not been perfectly enforced: in the data, forest coverage on private properties is approximately 44 percent (see Subsections 3.4 and 5.3).[6]

Exploring these policy interventions using my framework yields three main findings. First, taxes can be effective in avoiding deforestation. In response to a perfectly-enforced tax of US$ 42.5 per hectare per year on agricultural land, farmers would be willing to maintain 80 percent forest coverage on private properties as opposed to the 44 percent forest coverage observed in the data. The 36 percent difference corresponds to approximately 27.7 million hectares, which is about 5.5 years of the worldwide net forest loss observed over the past decade. Because farmers' average gross revenue per hectare in 2006 was US$ 120/ha, it should be no surprise that many farmers would not be willing to use land for agriculture with such a tax.[7] In addition, policies that *only* target small landholders are not able to promote substantial conservation. The extremely unequal distribution of land in the Amazon suggests that payment programs are unlikely to significantly reduce local poverty and deforestation simultaneously.

Second, the existing legislation (in the form of the '80 percent rule') would be expensive for local farmers if it were perfectly enforced, resulting in at least US$ 4.41 billion per year of lost farmer surplus. A tax of US$ 42.5/ha would also result in 80 percent of forest cover, but be substantially less expensive: farmers' lost surplus would be approximately US$ 479 million per year, provided the tax revenues were redistributed to them.[8] This corresponds to a cost saving from the land use tax of approximately 90 percent of the cost of a perfectly enforced '80 percent rule,' which is

[6]The establishment of protected areas on public lands is one of the leading forest conservation policies in the world, and in Brazil in particular (Pfaff, Robalino, Herrera, and Sandoval (2015)). I do not estimate causal impacts of protected areas on deforestation because my focus is on policies that affect land use in private properties (though I do allow for spillover effects – see discussion in Section 4.2). The type of payment program that I consider are payments to avoid deforestation. Although payments to replant forests are important, they are not studied here.

[7]The standard deviation of the gross revenues in 2006 was US$ 560/ha. The high dispersion helps explain why a considerable amount of land might still be farmed under the US$ 42.5/ha tax. Note that instead of a perfectly enforced tax, one may interpret US$ 42.5/ha as the expected tax that farmers would pay.

[8]Tax revenues would have been approximately US$ 658 million per year (0.37 percent of the Brazilian federal budget for 2006).

substantially higher than the cost saving estimates from allowance trading in pollution markets, ranging from 20 to 47 percent (Schmalensee and Stavins (2017)). The '80 percent rule' would be substantially more expensive than taxes because the more productive farms would use less land for agriculture and so forgo more profits. Although land-use taxes and payment programs differ in several respects (including the distribution of preservation costs, and practical implementation issues), they share the same predictions in terms of land use and lost surpluses in the present context. As such, payments of US$ 42.5/ha would yield the same forest cover as taxes, but would require US$ 2.61 billion per year of transfers to farmers (approximately 1.45 percent of the Brazilian federal budget for 2006).[9]

Third, by combining the estimated demand for deforestation with the geographic distribution of the carbon stock in Brazil, I obtain a 'supply of avoided emissions.' If a carbon tax of (or a program paying) US$ 1 per ton of CO_2 per year were implemented, farmers would be willing to avoid emissions of approximately 4.17 billion tons of carbon. That corresponds to about 4.5 years of worldwide emissions from land use change during 2002 to 2011 (IPCC (2013)). Given the low agricultural returns and the large stock of carbon on the ground, a carbon tax set at the social cost of carbon (estimated to be US$ 21/tCO_2 for 2010 according to Greenstone, Kopits, and Wolverton (2013), and US$ 18.5/tCO_2 for 2015 according to Nordhaus (2014)) could virtually eliminate all agricultural land in the Amazon.

The rest of the paper is organized as follows: Section 2 places the analysis in the context of the related literature. Section 3 provides relevant background to the Brazilian Amazon. Section 4 presents the empirical framework and a detailed discussion of the identification strategy. Section 5 presents the data. The estimated regressions are shown in Section 6. Sections 7 and 8 discuss the estimated demand for deforestation and the policy implications, respectively. Section 9 concludes.[10]

2 Related Literature

This paper builds on important prior studies that develop empirical land use models and analyze deforestation. The IPCC (2007, 2013) and the Stern Review (2007) make extensive use of

[9] A perfectly targeted policy making payments *only* to those who would deforest their lands and *not* paying those who would *not* deforest would require less than half of the non-targeted program transfers: US$ 1.18 billion per year. The geographic pattern of deforestation under taxes or payments would also be different from the pattern under the '80 percent rule' being more concentrated in the South Amazon, which is arguably the most productive area. As a result, forests in the central regions of the rainforest would have been less fragmented, which may be advantageous from a biodiversity point of view.

[10] The Supplemental Material complements the main text with various robustness exercises and a detailed explanation of the construction of the variables used in the paper.

'engineering/costing' models, in which the values of alternative land uses are calculated from the revenues and costs of the different alternatives of a representative farm.[11] Although that approach proves fruitful, it does not incorporate unobserved heterogeneity across farms. As a result, all farmers in a region would prefer to not deforest when taxes (or payments) reduce the *average* value of agricultural land sufficiently compared to the *average* value of forested land. When farms are heterogeneous, however, the marginal unit of land in a region differs from the average unit and so the estimated impacts on deforestation and the estimated costs of policies may be biased.

Revealed-preference methods incorporating unobserved heterogeneity were first developed in the seminal contributions of Stavins and Jafee (1990) and Stavins (1999). Typically, existing studies estimate reduced-form parameters of farmers' land use choice models using short panel data, exploiting variables with a high degree of variation across time, such as prices or revenues; and different empirical approaches identify farmers' short-run or long-run responses, depending on the time frame covered in the data.[12]

The distinction between farmers' short-run versus long-run responses is important in order to evaluate the performance of alternative policies. As noted already, policy makers may prefer implementing policies that can be put into effect for a long period of time. Estimates obtained from short panel data, however, exploiting, say, year-to-year variation in prices may not provide a reliable indication as to how farmers would react to a counterfactual permanent policy change. In other words, counterfactual simulations may suffer from an external validity problem.

One possible solution is to estimate a forward-looking dynamic structural model of land use choice. In a recent innovative contribution, Scott (2013) implements a structural model in a US setting and finds that dynamic reduced-form models (i.e., with myopic agents) likely understate long-run land use responses. Structural dynamic models require access to rich data that are not always available, especially in developing countries, where most of the worldwide deforestation has been occurring (FAO (2016)). When access to data is somewhat limited, another approach is necessary (Timmins and Schlenker (2009), Brady and Irwin (2011)).

In this paper, I exploit regional variation in transportation costs as a means to recover farmers' responses to permanent policies. The first step of my strategy builds on a growing literature

[11] See Kindermann *et al.* (2008) for a thorough investigation of different large-scale models in the context of potential REDD+ programs; Nepstad *et al.* (2007) for REDD+ in the Brazilian Amazon; and Lubowski and Rose (2013) for a recent survey of the literature.

[12] See Lubowski, Platinga and Stavins (2006), Busch *et al.* (2012), Mason and Platinga (2013), and, for a recent review of the literature, Brady and Irwin (2011). Stavins and Jaffee (1990) use the parameter estimates to simulate the impacts of public infrastructure investments; similarly, Stavins (1999) simulates a carbon sequestration model.

that estimates the determinants of land use.[13] The typical exercise in that literature involves regressing deforestation on covariates using ordinary least squares (OLS), flexible methods such as matching, or fixed-effect methods using panel data. A common focus has been on the impacts of roads on deforestation; existing studies do not attempt to estimate how farmers would respond to counterfactual incentive-based policies.

Compared to that literature, the first part of my strategy adds a plausible instrumental variables approach to address the potential endogeneity of roads and measurement errors in transportation costs, in a similar spirit to Chomitz and Gray (1996) (see Subsection 4.2 for a detailed discussion of the identification strategy). In addition, I allow for heterogeneous impacts across municipalities through the use of quantile regressions. Conditional on observables, a highly deforested location may be well-suited to agriculture in terms of unobservables so that transportation costs would have to increase considerably to reduce the amount of agricultural land; better preserved locations, in contrast, may be more sensitive to changes in transportation costs. An implication is that the relative value of the agricultural land also likely differs at the upper and lower tails of the conditional distribution of deforestation. These differences may lead to non-trivial impacts on the aggregate costs of the policy interventions. My results (shown in details in Sections 6 and 7) confirm this: the estimated coefficients differ across quantiles, and have important impacts on the total costs of policies.[14]

A related recent literature focuses on the impacts of roads on deforestation and on local economies using treatment effects methods. Those studies construct treatment and control groups carefully based on regions (say, census tracts) that received road investments versus regions that did not. Examples include Banerjee, Duflo and Qian (2012) for impacts on local GDP in China, and Pfaff and Robalino (2013) for impacts on deforestation in the Brazilian Amazon. Although those approaches are appealing, they are not well-suited for my purposes here. First, the estimated differences in land use between places close to and distant from local roads can explain the *differential* impacts on the groups, but I need to estimate the *overall* impacts of roads on land use to back out farmers' private values. In addition, they do not take into account improvements in roads elsewhere in the transportation network (except by use of adjacency matrices). I instead consider roads as a network and estimate aggregate impacts of transportation networks in a spirit similar

[13] See Chomitz and Gray (1996), Pfaff (1999), Andersen *et al.* (2002), Chomitz and Thomas (2003), Brady and Irwin (2011), and the literature cited therein.

[14] Specifically, the standard two stages least squares estimator (2SLS) cannot capture heterogeneous responses to changes in private values, and overestimates the total costs of policies. According to the 2SLS estimates, a land-use tax that gives rise to 80 percent of forest cover would cost approximately US$ 786 million per year, which is 64 percent more than the estimated costs based on the quantile approach.

to Donaldson and Hornbeck (2016).

Finally, a growing literature studies recently-implemented 'payment for ecological services' programs. Those studies use treatment effect techniques and find mixed results. Possible explanations include program design, and the fact that evaluations have taken place in countries – mainly Mexico and Costa Rica – in which deforestation rates were declining over the period of the program (Alix-Garcia and Wolff (2014)). The current paper complements that literature by providing a framework for estimating the potential effects of policies yet to be implemented.[15]

3 Background to the Brazilian Amazon

3.1 A Brief History of the Occupation of the Amazon

Before the 1960s, the Amazon was barely occupied. Open access to forestry was typical and local economic activity was based on subsistence and a few extraction activities, mainly rubber and Brazil nuts. Most of the municipal seats were established by late 1800s and early 1900s as a result of these local activities.[16] During the 1960s and 1970s, the military dictatorship promoted the occupation of the region with the explicit objective of securing national borders and integrating the region's economy. Hydroelectric facilities, mining, ports, and around 60,000 km of roads were constructed during this period. The first overland connection between Amazonia and the rest of the country was completed in 1964 – a highway linking Belem, an Amazonian state capital, and Brasilia, the country's capital city located in the central region. During the 1980s, an economic recession and hyperinflation led the government to cut investment. Then, after the 1990s, ecological concerns started to shape the policies in the Amazon. IBAMA (the Brazilian Environmental Protection Agency) was created in 1989 to monitor and enforce environmental policies. In 1996, the required share of forest cover on private land in the Amazon increased from 50 percent to 80 percent.

Deforestation rates increased substantially since the 1960s, especially during the 1990s and early 2000s (INPE (2017)). After the peak of deforestation in 2004, when an area almost the size of Belgium was deforested in a single year, the Brazilian government launched a new and ambitious conservation program that focused on two main areas: improvements in remote sensing-based monitoring and the expansion of protected areas. Then, in 2008, Brazil issued a list of municipalities

[15] See Pattanayak, Wunder and Ferraro (2010), Jack (2013), Alix-Garcia and Wolff (2014), Simonet *et al.* (2015), Jayachandran *et al.* (2017), and the literature cited therein. Simonet *et al.* (2015) provides the first impact analysis of a small-scale PES pilot project in the Brazilian Amazon. They find the program has decreased the deforestation rate by about 50 percent, with no evidence of leakage effects, and that the monetary gains from the avoided carbon emissions largely exceeds the implementation costs.

[16] Source: http://cidades.ibge.gov.br/xtras/home.php

for the first time, updated annually, that were to be subject to more rigorous monitoring and stricter policy actions. The deforestation rate significantly slowed down after 2009.[17]

3.2 Area Occupied

Figure 1 shows the map of Brazil in the left panel, along with the location of the Amazon rainforest, the political divisions and the names of the Amazonian states. The right panel includes the deforested area in 2006 according to satellite images (produced by the Brazilian National Institute of Space Research – INPE). Most of the deforested area is concentrated in the southern and eastern parts of the Amazon, normally referred to as the 'Arc of Deforestation.'

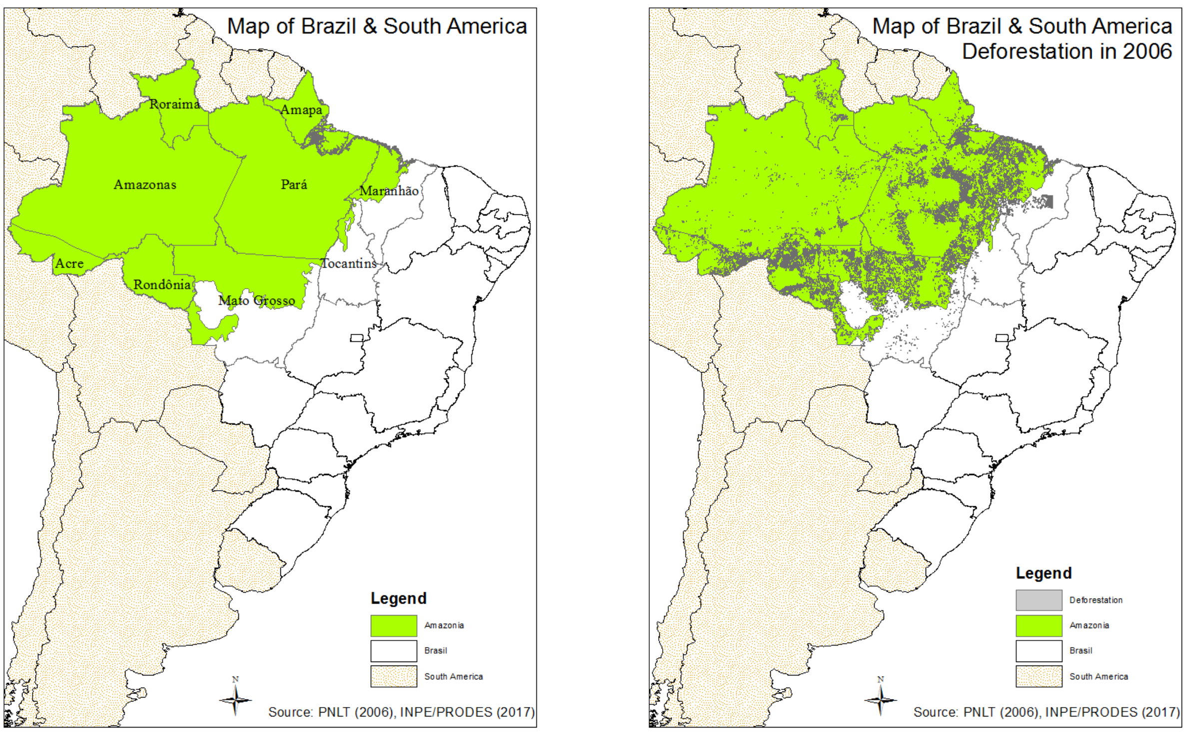

Figure 1: Deforestation in 2006

Private land occupies about 18 percent of the Amazon, but the proportion varies depending on the region: it occupies 45 percent of the *South Amazon*; 19 percent of the *Eastern Amazon*; and 4.5 percent of the *Western Amazon*.[18] Conservation Units and Indigenous Reserves accounted

[17] The average annual deforestation between 1988 and 2006 was 1.8 million hectares. It stabilized after the policy changes: the average annual rate fell to 0.6 million hectares during the period 2009–2017 (INPE (2017)).

[18] The *South Amazon* comprises the states of Rondônia and Mato Grosso; the *Eastern Amazon*, the states of Pará, Amapá, part of Tocantins and part of Maranhão; and the *Western Amazon*, the states of Amazonas, Acre and

for approximately 44 percent of the Amazon by 2010 (INPE (2017)). Overall, approximately 38 percent of the region consists of unprotected public land.[19]

Most of the private land is used for pasture (about 49 percent) and the grazing cattle are used mainly to produce beef. Brazil has the largest number of cattle in the world (171 million cattle in 2006, of which approximately 35 percent were reared in the Amazon). It is the second largest producer of beef and is the largest beef exporter. Ten percent of the private properties in the Amazon are occupied by crops. Soy is the most important crop (occupying about 22 percent of the crop area), followed by corn (11 percent), manioc (11 percent), rice (8.4 percent) and other types of beans (4 percent). Brazil also is the largest exporter of soybeans in the world. Cropland has expanded lately in the South Amazon, where most of the deforestation has been occurring. Forests occupy about 37 percent of the private land, including forests that are not being exploited and also managed forests. Among the forestry products, the most important in terms of the value of production in 2006 were açaí, an Amazonian fruit (41 percent), and timber (39 percent).[20]

There are important differences between logging activities and agricultural production. First, logging activities cause *forest degradation* (i.e., forest cover that, while not intact, has not yet been totally removed), while agriculture causes *deforestation* as it requires complete land clearing. Second, although annual forest degradation and annual deforestation areas are comparable in magnitude (INPE (2017)), agriculture production is the activity that most affects total forest cover in the long term. Forest degradation appears to occur mostly as a result of a single selective logging event and is typically associated with low-intensity forest damage (Pinheiro *et al.* (2016)). Signs of degradation may not be visible even one year after being detected in the satellite imagery. Deforestation, in contrast, accumulates over time: the total accumulated deforested area in 2006 was 14 percent of the Legal Amazon in 2006 (INPE (2017)).[21]

Roraima. The *Legal Amazon* is an administrative area in the northern part of Brazil that includes the nine states indicated in Figure 1.

[19] The unprotected public land can still be occupied and claimed by squatters. Despite this fact, most farmers have land titles (85 percent), and the proportion of farms with no land titles is higher among small landholders (20 percent). Small landholders in the present paper are those who own farms less than 5 hectares in size.

[20] The production of soybeans and corn is located mostly in the South Amazon and is directed to international markets. Manioc, rice and beans are consumed domestically, with manioc being more concentrated in pristine areas, possibly for subsistence. The logging industry is located along the South and Eastern Amazon and it directed 36 percent of its production to international markets in 2009 (data sources: USDA (www.fas.usda.gov/psdonline/), and the Brazilian Agricultural Census for 2006).

[21] Based on remote-sensing data for 2008, Almeida *et al.* (2016) estimate that approximately 90 percent of the total deforested area in the Brazilian Amazon is used for agriculture (pasture and cropland), 3 percent corresponds to mining, urban areas, and others, and the remaining 7 percent is unobserved (i.e., areas whose land cover cannot be interpreted due to cloud shade or smoke from recently burned areas).

3.3 Transportation Network

Figure 2 presents key geographic information relevant to the analysis. The top left panel of Figure 2 shows the navigable rivers and the main ports. Rivers have always been important in the Amazon, especially in the western region, where they are the only means of transportation for the local populace. The top right panel of Figure 2 presents the railroads and the Amazonian state capitals. Railroads are not very prevalent in Brazil, are concentrated in the southeast, and mainly connect into ports. The main ports in the country are also located in the southeast, the most important being the Port of Santos and the Port of Paranaguá. Not only is the infrastructure of these ports better, the roads linked to them are also of higher quality than in the rest of the country, making them a more attractive option for exporters than the ports in the north.

The bottom left panel shows the location of roads, distinguishing paved from unpaved roads. Most of the roads in the Amazon are unpaved (89 per cent, according to the Ministry of Transportation). The few paved roads in the region tend to connect the main state capitals. The bottom right panel combines the transportation network and the deforested area in 2006, making apparent the spatial correlation between them.

3.4 Legislation and Penalties

If a farmer wants to clear a fraction of his land, he needs to hold many licenses and authorizations, including a detailed plan of management that must be approved by the state and the national environmental protection agencies. The requirements are costly and time-consuming to fulfil, and may take several months to be approved (Hirakuri (2003)). Sanctions for forest-related violations include fines ranging from US$ 2,300 to US$ 23,000 per hectare, the seizure of products and equipment, and the suspension of activities. The fines are extremely costly to farmers in view of their average gross revenue per hectare, which was US$ 120/ha according to the Agricultural Census of 2006.

There is evidence that the legislation has not been fully enforced. For example, between 2005 and 2009, IBAMA applied 24,161 fines totaling about US$ 7.34 million, but the revenues collected from these fines were only 0.6 percent of their total value (TCU (2009)). Perhaps more importantly, the proportion of deforested area (according to satellite images) that received fines was small before 2006: approximately 0.15 percent in 2003, 0.1 percent in 2004, 1.2 percent in 2005, and 7.9 percent in 2006.[22] Furthermore, Brito and Barreto (2006) analyzed a sample of 55 court cases involving

[22] Estimates provided by IBAMA. The fraction of deforested areas where fines were levied increased substantially after 2006: 49 percent in 2007; 44 percent in 2008; 51 percent in 2009, and 24 percent in 2010. It seems to be the

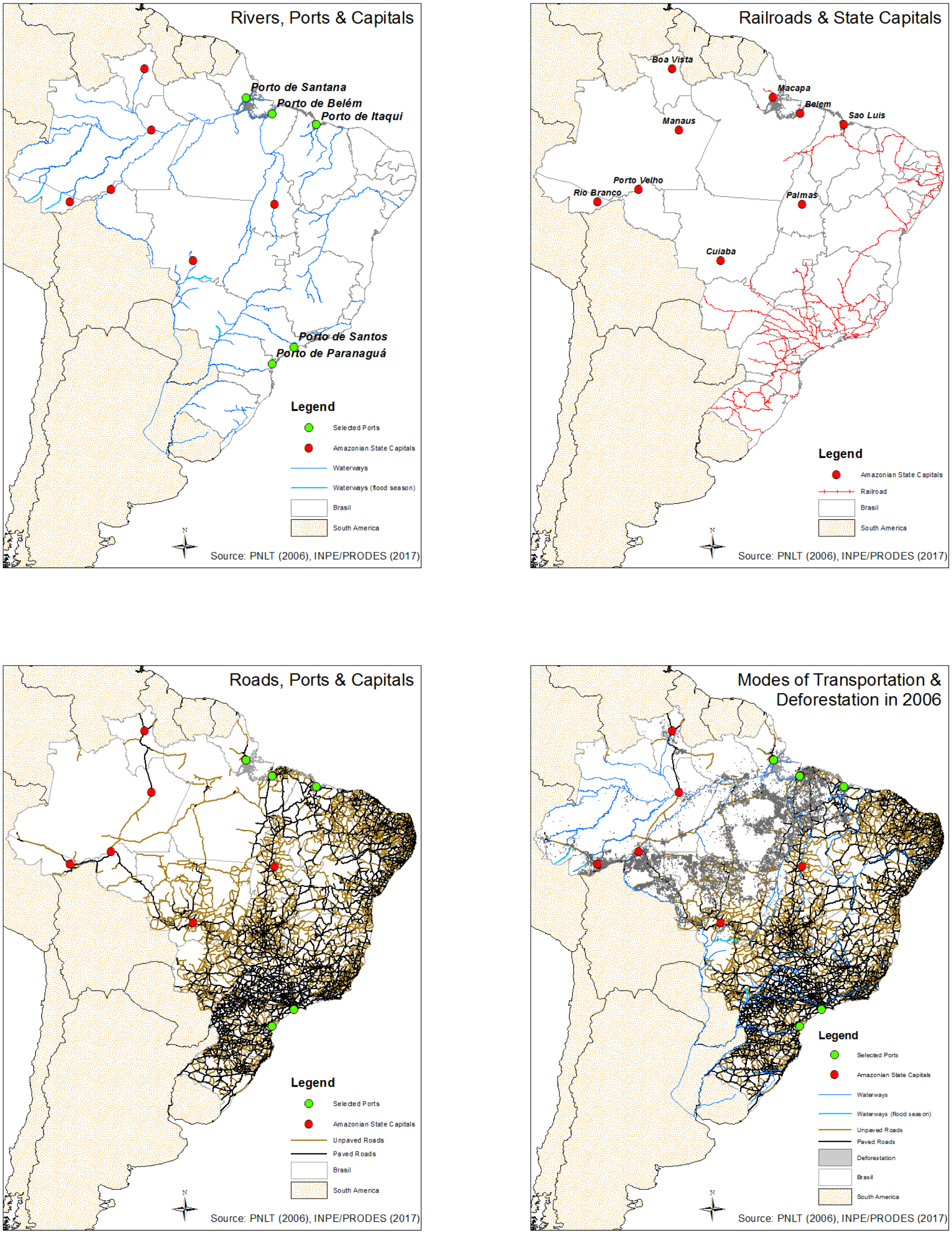

Figure 2: Transportation Network and Deforestation

environmental violations in the forest sector in the Pará State between 2000 and 2003 and found that only 2 percent of the offenders were criminally liable.

Historically, the expected cost of punishment seems to have been low (at least up to 2006), in spite of the recent increase in monitoring efforts after 2004. Therefore, one might expect farmers to have slashed-and-burned to clear the land without authorization. (IBAMA staff estimate that more than 90 percent of deforestation is indeed illegal.)[23]

4 Model and Estimation

In this section, I present a stylized model to guide the empirical analysis. Before setting out the details of the model, several remarks about the general formulation are in order. First, deforestation will be thought of as the share of agricultural land on private properties. I assume the land was originally forested, so that clearing it for agriculture is equivalent to deforesting it. The remaining area includes managed forest (which can be used to produce timber or other forest products) and forest that is not being exploited.[24]

Second, the available data are already aggregated up to the municipal level. Thus, it is not possible to distinguish between a model in which farmers choose the share of agricultural land and a model in which there is a continuum of farmers making binary choices between agricultural and forest land. The typical exercise in the literature that estimates the impact of roads on deforestation assumes a binary choice model for individual landowners' decisions and aggregates their choices up to the municipality level (Pfaff (1999)). I follow that literature in order to make my procedure comparable to existing research and because the binary choice model is convenient when interpreting the results.[25]

Third, the policies I consider seek to influence the way farmers use their land. For this reason, I focus on landowners' choices *within* private properties. It makes little sense to tax (or pay for) land that no one owns; and the '80 percent rule' does not apply to public land. Deforestation of public land is an important problem in the Amazon, but one that I do not investigate here. I also split the sample into different farm sizes and conduct the analysis separately for each sub-group.

result of redoubled government efforts to slow down deforestation (see Assunção, Gandour and Rocha (2013)).

[23] This is based on informal conversations with IBAMA staff. IBAMA does not have the official numbers yet because the state agencies responsible to supply the information to the national system do not provide data on regularized deforested areas.

[24] Although most of the deforestation took place in the past, transportation costs decreased over time as the transportation network evolved. The incentives to deforest in response to these cost reductions has therefore increased over the years.

[25] The aggregated nature of the data prevents me from considering local neighbor interactions. See Robalino and Pfaff (2012) for an analysis of the importance of neighbor interactions based on detailed micro data for Costa Rica.

Separating the groups allows for diminishing (or increasing) returns to agricultural land that may affect farmers' private valuations. It may also be informative for policy makers: to the extent that policy makers view payment programs as a way to reduce poverty, they may want to adjust payments to small landholders.[26]

Finally, from a policy perspective, although land-use taxes and payment programs differ in several respects (including practical implementation issues and the distribution of preservation costs), they share the same predictions for land use decisions in the present context, as will be clear below. For this reason, I lump them into one policy and refer to them simply as "taxes," unless stated otherwise.

Next, I present the details of the model, and describe the identification strategy.

4.1 Model

Take a parcel of land i that belongs to a farm of size s located in municipality m. Assume there is a continuum of such parcels, and for each parcel, the farmer decides whether or not to clear it for agriculture. Let P_{ims} be a vector of input and output farmgate prices and X_{ims} be a vector of other determinants of land use (e.g., productivity factors). Define $\Pi^a(P_{ims}, X_{ims})$ as the expected discounted present value of current and future profits obtained by using the parcel for agriculture, and let $\Pi^f(P_{ims}, X_{ims})$ be the corresponding value obtained from leaving the plot as managed forest. The agricultural value Π^a incorporates upfront conversion costs and expected penalties for illegal deforestation (when applicable). The forest value Π^f includes profits from forest products (e.g., wild fruits and timber), the option value to deforest in the future, as well as possible non-pecuniary benefits. Let Y_{ims} equal one if the plot i is cleared and zero otherwise. Then,

$$Y_{ims} = 1\left\{\Pi^a(P_{ims}, X_{ims}) > \Pi^f(P_{ims}, X_{ims})\right\},$$

where $1\{.\}$ is the indicator function.[27]

[26] Affecting land use decisions on private land is an important way to promote conservation, considering that private properties occupy about 18 percent of the Amazon. More importantly, deforestation has been more intense in the states of the South Amazon (the states of Rondônia and Mato Grosso, see Section 3) where private properties occupy about 45 percent of the total area.

[27] One may interpret Π^a and Π^f as choice-specific value functions of a fully dynamic model. A structural dynamic model would separately identify and estimate the different components of Π^a and Π^f (current payoff, conversion costs, continuation values, and so on); see, e.g. Scott (2013). Because I do not estimate a structural dynamic model, the estimated parameters of the choice-specific values are not invariant to certain policy changes. While the framework allows me to estimate the effects of permanent changes in these values, it cannot estimate, for instance, the impact of a change in the volatility of timber prices, as this affects continuation values (in particular, the option value to deforest) in a way that the "reduced-form" payoff function cannot capture in the cross-sectional data. I am grateful to the Editor and an anonymous referee for pointing that out.

The vector of determinants of land use can be decomposed as $X_{ims} = (X_m, U_m(s), \varepsilon^x_{ims})$, where X_m is a municipality-level vector of observed productivity shifters, such as soil quality and other agroclimatic conditions, as well as government monitoring efforts to deter illegal deforestation; $U_m(s)$ is a municipality-level unobserved productivity shock; and ε^x_{ims} captures farmers' unobserved idiosyncratic abilities, effort and the deviations from both X_m and $U_m(s)$ within m. Because the empirical analysis is conducted separately for each farm size, it is possible to allow the unobservable $U_m(s)$ to be indexed by the size of the farm, which allows for a richer model than the usual municipality random effects model. That is, a municipality may be suitable for agriculture for large farms but less good for small landholders.

I assume farmers are price takers, that all production is sold in nearby markets or exported directly, and that a no-arbitrage condition holds. These assumptions imply that local prices are determined by the international price minus the transportation cost to the nearest port, i.e., $P_{ims} = \overline{P} - TC_{ims}$. The transportation cost TC_{ims} can in turn be decomposed into two parts. The cost to transport a product from the municipal seat to the nearest port is denoted by TC_m; a proxy for this variable is observed in the data. The deviation of the farm's transportation cost to TC_m is denoted by ε^t_{ims}, and is unobserved by the econometrician but observed by the farmer.[28]

Although the costs to transport different products may not be equal, they are likely to be proportional: all products use the same transportation network and reach the same ports (under the no-arbitrage condition). Therefore, the transportation costs of different products should be highly collinear, which makes it difficult to separately identify their impacts on deforestation. I therefore proceed with a single measure for transportation costs to reflect differences in local prices. The exact proxy for TC_m is explained in Section 5.[29]

The existing literature typically projects the difference between Π^a and Π^f on the municipal-level variables $(TC_m, X_m, U_m(s))$ and collapses all individual heterogeneity into a single scalar, ε_{ims}. In the present case, the model reduces to

$$Y_{ims} = 1\left\{X_m\beta_s - \alpha_s TC_m + U_m(s) - \varepsilon_{ims} > 0\right\},$$

where the coefficients can be different for different farm sizes. In addition, an extreme value

[28] As discussed in Section 3.2, the most important products in the Amazon are exported (with the exception of manioc). Informal conversations with farmers in the industry (particularly, the National Association of Soybeans Producers, as well as the beef producers) suggest that the price farmers effectively receive is the price at the port minus the costs to transport the product (minus a margin for the intermediaries). Given that information about intermediaries is difficult to obtain, I leave an investigation about their potential impact on deforestation for future research.

[29] Castro (2003) investigates freight values in Brazil for the period 1997–2003 and finds evidence that bulk products and sacks have similar transportation costs (because costs depend mostly on the weight of the product, and not on the type of packaging).

distribution for ε_{ims} is typically imposed.[30] Let $Y_m(s)$ be the aggregated share of agricultural land within farms of size s in municipality m. The resulting logit model can be estimated after taking the differences of log shares as:

$$\log\left(\frac{Y_m(s)}{1-Y_m(s)}\right) = X_m\beta_s - \alpha_s TC_m + U_m(s). \tag{1}$$

Note that farm size, s, is not an explanatory variable in equation (1): I do not attempt to explain deforestation by exogenously varying the size of the farms. Although the endogeneity of farm sizes has been discussed extensively in the literature, particularly in the literature that estimates impacts of cultivated agricultural area on rural productivity (see, e.g., Foster and Rosenzweig (2011) and the references cited therein), there is no problem of endogeneity of farm sizes when estimating equation (1).[31]

The typical exercise in the literature estimates equation (1) using OLS (Pfaff (1999)). My procedure builds on the standard approach, extending it in two ways. First, transportation costs are instrumented for using straight-line distances to the main destinations, which addresses the potential endogeneity of roads and measurement error in transportation costs. In Subsection 4.2, I discuss reasons why transportation costs to the nearest port should be instrumented for and under what conditions straight-line distances to the main destinations are expected to be valid instruments.

Second, I use quantile regression instead of mean regression. As noted previously, two observationally equivalent locations (in term of X and TC) may respond differently to changes in transportations costs. On the one hand, a highly deforested location may be well-suited to agriculture in terms of unobservables so that increases in transportation costs may not significantly reduce the cultivated area. On the other hand, a preserved location may be so unsuitable for agriculture that small increases in TC could substantially reduce deforestation. The impacts of roads therefore likely differ at the upper and lower tails of the conditional distribution of deforestation. An implication of this is that the relative value of the agricultural land also likely differs at the upper and lower tails of the conditional distribution: some locations may be more sensitive to taxes than others and so may face higher costs (lost surpluses) when taxes are imposed. In turn, these differences may lead to non-trivial impacts on the aggregated costs of policy interventions.

[30] Given the linear specification, the international prices $\overline{P}$ are incorporated into the constant term, and the idiosyncratic shocks ε_{ims} are composed of $\varepsilon^x_{ims} - \alpha_s\varepsilon^t_{ims}$. The variance of ε_{ims} may differ for different farm sizes s, which in turn may affect the scale of the estimated model parameters. This is a common aspect of discrete choice models.

[31] To identify impacts of farm size on the profitability of farms in India, Foster and Rosenzweig (2011) make use of the fact that a substantial fraction of the households in their data divided (or received inherited) land because a parent died. This source of exogenous variation together with the panel data structure are exploited to handle the endogeneity of farm sizes. I have no such exogenous variation in the current data set.

To allow transportation costs to affect the entire conditional distribution of deforestation, I use a quantile model. Instead of estimating equation (1), I estimate:

$$\log\left(\frac{Y_m(s)}{1-Y_m(s)}\right) = X_m\beta\left(U_m(s)\right) - \alpha\left(U_m(s)\right) \times TC_m, \tag{2}$$

where $U_m(s)$ is now normalized to have a uniform distribution on $[0,1]$. Equation (2) is a random coefficients representation of the quantile function. More specifically, following Chernozhukov and Hansen's (2013) terminology, the function $u \mapsto X_m\beta_s(u) - \alpha_s(u) \times TC$ is the "quantile treatment response" (QTR) function. The QTR function is strictly increasing and continuous in $u \in [0,1]$, so that a location more prone to agricultural activities is associated with a higher value of u. The coefficients on X and TC can depend arbitrarily on both the farm size s and the quantile u, which implies heterogenous effects on deforestation. This flexibility relaxes the role of both the single-index restriction and the logit assumption in determining the shape of the demand for deforestation. From now on, I change notation slightly and denote the coefficients by $(\beta_{su}, \alpha_{su})$.

Because the transportation cost is not exogenous, the conventional quantile regression estimator is inconsistent for estimating the QTR function. For this reason, I estimate equation (2) using the instrumental variable quantile regression (IVQR) estimator proposed by Chernozhukov and Hansen (2008).

Demand for Deforestation. Taking the logistic function $h(x) = \exp(x)/(1+\exp(x))$, the share of agricultural land for farms of size s in municipality m at a given quantile u is given by $h(X_m\beta_{su} - \alpha_{su}TC_m)$. The effect of raising the private value of the forested area (relative to the value of agricultural area) by US\$ t per hectare on farmers' land-use decisions is given by

$$Y_m(s,t) = h\left(X_m\beta_{su} - \alpha_{su}\left(TC_m + \frac{t}{q_m(s)}\right)\right), \tag{3}$$

where $Y_m(s,t)$ is the counterfactual share of agricultural land, and $q_m(s)$ is the quantity (in tons) of agricultural output sold per hectare. I define the *demand for deforestation* for farms of size s in municipality m as the product of the total area they occupy and the counterfactual share $Y_m(s,t)$. The total demand aggregates over s and m.[32]

[32] This structure can be extended to consider multinomial choice models (e.g., forest *vs.* crop *vs.* cattle ranching), and in principle, variables other than TC_m can be used to capture variation in private values (e.g., data on agricultural potential to identify crops *vs.* livestock). Yet, in order to be useful, any such variable must satisfy three requirements: (a) it must affect farmers' decisions significantly, i.e., it must have a coefficient that is different from zero; (b) it must be measured in dollars in a way that can be converted into the appropriate units; and (c) it must be able to capture persistent differences in the private returns to land use. None of the variables in X_m in the present data set satisfies all three requirements.

Two aspects of the demand function require discussion. First, following Chernozhukov and Hansen's (2013) terminology again, this demand satisfies the "rank invariance" assumption. Rank invariance is a common assumption in the applied literature and preserves the intuitive notion that, conditional on observables, a relatively highly deforested location in the data (i.e., a location associated with a high rank u) remains a relatively highly deforested location under alternative counterfactual policies (i.e., it preserves the rank u).[33]

Second, because the data are aggregated up to the municipality level, and because there are hundreds of products being produced in the Amazon, some care is needed in defining $q_m(s)$. I selected the most representative products (those discussed in the Subsection 3.2) and constructed a local productivity index (in which the weights are the proportions of the area utilized for each product). The underlying assumption here is that once the land is cleared for agriculture, it is used in fixed proportions for pasture and for the main crops: the proportions are allowed to differ across municipalities, but they are fixed within the municipality.[34]

4.2 Identification Strategy

Endogeneity. There are several reasons why one needs to instrument for transportation costs in land-use regressions. First, they are likely measured with an error. The proxy for transportation costs is defined here as the minimum unit cost (US$/ton) to transport 1 ton of goods to the nearest port using the most cost-effective route. It is a common proxy used in the literature (Allen and Arkolakis (2014), Donaldson and Hornbeck (2016)), but it may not provide an accurate measure of the real costs that farmers incur and so is potentially mismeasured. If the measurement error is classical, it may induce an attenuation bias in the OLS estimates.

Second, previously deforested regions may have a higher demand for improvements in local infrastructure conditions, including more and better roads, which leads to reverse causality in cross-sectional data. Third, roads may have been built in response to profitable agricultural conditions. As a common example, unobservable (to the econometrician) soil quality for agriculture in a given

[33] Empirical applications that estimate QTR functions under the rank invariance assumption include Hausman and Sidak (2004), Chernozhukov and Hansen (2008), and Lamarche (2011).

[34] I also consider a second index that includes only the main crops and ignores pasture land. This severely restricts the substitution patterns among land uses within municipalities and so provides a conservative upper bound on the demand for deforestation. More general substitution patterns could be recovered by exploiting choice-specific variables that shift the value of each type of land use independently of the value of the other options (Berry and Haile (2014)), but there is no variable satisfying such a requirement in the present data set. I therefore choose to be agnostic in terms of the way the agricultural area is divided when estimating the impacts of TC_m on deforestation, and reported the results for both indices. I also examined whether the indices q_m respond to TC_m, and found no such evidence: farmers seem to adjust the extensive margin (land use), but not the intensive margin (yields), which is consistent with Roberts and Schlenker (2013). (See the Supplemental Material.)

location may have induced both deforestation and road construction to access the location. Both the simultaneity and the omitted variable problems may lead the OLS estimates to overstate the impact of transportation costs.

In the present case, the omitted variable problem does not necessarily lead to an upward bias. As mentioned in Subsection 3.1, early occupation of the Amazon was based on the extraction of rubber, and regions that are well-suited for the growth of rubber trees (*Hevea brasiliensis*) are not necessarily well-suited to agriculture. The soil quality in the Amazon is actually poor for agriculture in most regions (see Section 5). Because good navigable rivers might have been used and unofficial roads might have been built in the past to access valuable trees, but more recent roads (and their recent improvements) may have been directed to agricultural regions, the direction of the bias of the OLS estimator is not clear *ex-ante* (Pfaff *et al.* (2009)).

Instruments. I use straight-line distances to the nearest port and to the nearest state capital as instruments for transportation costs. I now discuss (a) why one should expect straight-line distances to be strong instruments – this is testable, and (b) under what conditions one should expect the instruments to satisfy an exclusion restriction condition.

First, it is evident that distances to the nearest port should correlate with the costs to the ports. Furthermore, to the extent that state capitals are connected to better transportation infrastructure (see Subsection 3.3), a location close to a state capital should have lower costs (*ceteris paribus*) of reaching the ports. Therefore, the distance to the nearest capital should also be positively correlated with transportation costs.

The conditions under which the instruments satisfy the exclusion restriction are more involved. I start following the discussion presented by Chomitz and Gray (1996). Because locations of major towns – in the present case, ports and state capitals – were determined by geography and historical reasons long before the expansion of the roads in the 1970s, I can construct an exogenous network of roads by linking the major centers with straight-lines.[35] The distances computed using the virtual network should be correlated with transportation costs to ports, because the location of the towns creates links between the major centers, but not the precise routing. Similar to the ports and state capitals, most of the municipal seats in the Amazon were established long before the occupation of the Amazon. Specifically, they were established by the late 1800s and early 1900s and – as discussed earlier – were not necessarily located in areas where agricultural activity was more valuable. It is

[35] All state capitals and ports used in this paper were established before or during the 19th Century, except for Porto Velho (founded in 1907).

conceivable therefore that the virtual road network is exogenous to the agricultural activities that took place in the Amazon after the 1970s. Given that using the virtual network and computing straight-line distances directly to the main destinations provides the same information, I opted for the simpler solution.

Although the virtual road network can be viewed as exogenous to recent agricultural activities, it is still possible that the straight-line distances correlate with factors that affect farmers' decisions to deforest. It is therefore necessary to control for those factors. As discussed in Subsection 4.1, farmers' decisions depend on productivity shifters, government monitoring efforts, and on farm-gate input and output prices. Once those factors are taken into account, straight-line distances do not influence farmers' choices. In the application, I control for differences in productivity using measurements of soil quality and various agroclimatic variables. I consider two proxies for monitoring efforts (which I discuss in more detail below): the number of fines issued for environmental infractions, and the distance to the nearest IBAMA office (the Brazilian Environmental Protection Agency). Variation in local prices is explained by variation in transportation costs to the nearest port, at least for tradable goods.

The instruments may be invalid if there are inputs or outputs whose prices are not fixed in the international market. In such a case, local market conditions may affect local prices and correlate with straight-line distances to the main destinations. Consider local labor markets: wages may have to increase as the municipalities are found further away from the nearest capital, all else equal, to compensate workers for working away from more desired locations. Municipalities further away from the capital may deforest less than a location close to the capital because of wage differences. If the wage differences are not controlled for in the regression, and correlate with the instruments, then the proposed instruments are invalid. A similar problem may occur if there are other non-tradable inputs and outputs.

To mitigate this problem, I include in the regressions factors that shift local demand and supply for non-tradable inputs and outputs that may correlate with straight-line distances. Specifically, I include the local population, the presence of power plants (mainly hydroelectric facilities), and local mining. While the local population shifts the supply of labor and increases the demand for non-tradables, power plants and mining shift both the demand for labor and non-tradables. Although one may be concerned with the endogeneity of population, including and excluding population in the regressions does not change the results significantly. I present the estimates in the Supplemental Material.

In addition, inter-related local markets may create spatial dependence in terms of farmers' decisions across municipalities. For instance, Assunção, Lipscomb, Mobarak and Szerman (2016) provide evidence that power plants affect land use decisions in the neighborhood of power plants in Brazil. To take this dependence into account, I also include spatially lagged regressors of the local demand and supply shifters among the covariates.[36]

To capture government monitoring efforts, I consider the distance to the nearest IBAMA office and the number of fines issued. Distance to IBAMA is intended to capture the possibility that monitoring and punishing farmers for illegal deforestation is more difficult for farms located in more pristine areas, i.e., the farther away the farm is, the less monitoring there will be, and so the more incentive the farmer will have to deforest. Ignoring this possibility may lead to the underestimates of the impacts of transportation costs.

Data on fines are publicly available after 2002 (see Supplemental Material). I consider the cumulative number of fines over 2002–2005, which may capture the recent increase in monitoring efforts. The inclusion of fines in the regressions leads to the usual simultaneity problem: the higher the deforestation level in a given location, the greater the number of fines imposed in that location. This causes an upward bias in the estimated coefficient on fines. The biases on the coefficients on TC_m caused by this simultaneity problem are less clear *ex-ante*; and it is a nontrivial task to find good instruments for environmental infractions in a cross-section of Amazonian municipalities. Against that, ignoring the number of fines in the regressions may lead to omitted variables bias. The direction of the omitted variables bias depends on the correlation between fines and the instruments for TC_m. In the data, this correlation is small, which suggests the omission may result in small biases. Indeed, the estimated coefficients on fines have the expected sign, but they are not statistically significant, their magnitudes are small, and the coefficients on costs to port are not substantially affected by the inclusion or the exclusion of fines (see Supplemental Material). This is consistent with the interpretation that the increased monitoring efforts were too recent to affect the total accumulated deforested land by 2006 substantially.

There are two more factors that potentially affect farmers' decisions to deforest and that may correlate with distances to ports and to state capitals: the proximity to protected areas (PAs), and the potential lack of property rights. Protected areas may have spillover effects that influence the value of nearby forestlands. Robalino, Pfaff, and Villalobos-Fiatt (2017) present evidence for Costa Rica showing that PAs may indeed cause deforestation in surrounding areas. To allow for

[36] In the Supplemental Material, I present a detailed discussion of other potential sources of spatial dependence, as well as some robustness exercises.

this potential mechanism, I include the distance to the closest PA as well as its spatially lagged value in the land-use regressions.

The potential lack of property rights is another possible determinant of land use. Historically, farmers had incentives to deforest as a way to secure their land tenure (Andersen *et al.* (2002)). It is conceivable then that the further farms are from a state capital, the less secure the land rights are, and so the more incentive farmers have to deforest – that is, the greater the distance, the larger the deforested area. To address this issue, I include a proxy for property rights in the regressions. In the Brazilian Agricultural Census, the best proxy for property rights is the proportion of private land with a land title – presumably, the higher the tenure security, the larger is the proportion of land with land titles.[37]

5 Data

In this section, I explain briefly how deforestation and transportation costs are measured. Then I present relevant summary statistics. The set of covariates that I use in the regressions includes: soil quality, temperature, rainfall, altitude, slope, local population, local mining, local power plants, total number of fines (up to 2005), distance to IBAMA, distance to protected areas, share of private land with land title, and spatially lagged variables for the local demand and supply shifters, as well as for distance to protected areas. A detailed description of the variables' construction is provided in the Supplemental Material.

5.1 Dependent Variable: Deforestation

The land use classification in the Brazilian Agricultural Census of 2006 is divided into several categories that I aggregated up to two: agricultural and forested land.[38] Agricultural land includes pasture and crops, while forested land aggregates managed forests and forests that are not currently being exploited. The categories of farm size considered here are: (a) small farms (those with fewer

[37] The tenure security proxy may be endogenous, as more deforestation may have led to a higher proportion of land titles: similar to the number of fines, the proxy may therefore suffer from simultaneity bias. Finding sources of exogenous variation for property rights within a country is an extremely difficult task – there are no clear instruments to hand. Yet, the inclusion or exclusion of the proxy for property rights in the regressions does not affect the estimates significantly (see Supplemental Material). Most farmers do have their land titles (85 percent) and it is possible that their land tenure status may not affect how their deforestation decisions relate to transportation costs.

[38] There is an alternative to using census data, namely satellite sensor data. However, remote-sensing data do not distinguish between deforestation on private and public land. Because the distinction is important in my analysis, I opted for using the census data. In the Supplemental Material, I present evidence showing that the census and the satellite data are consistent with each other in a restricted sample of municipalities in which the share of private land in the municipality area is large and the share of clouds/unobserved areas is small in the satellite imageries. That is, the two deforestation measures are consistent when they are most comparable. Thanks to an anonymous referee who suggested these comparisons.

than 5 hectares); (b) small-to-medium farms (those with an area between 5 and 50 hectares); (c) medium-to-large farms (those with an area between 50 and 500 hectares); and (d) large farms (those consisting of more than 500 hectares).

5.2 Endogenous Regressor: Transportation Costs

As a proxy for transportation costs, I use the minimum unit cost (US$/ton) to transport 1 ton of goods to the nearest port. This cost is calculated by combining information from the Brazilian transportation network for 2006 produced by the Ministry of Transportation for the National Highway Plan (PNLT (2006)), and the freight rate data collected by SIFRECA (the Freight Information System). The implementation used ArcGIS cost distance tools (see Allen and Arkolakis (2014) for an excellent description of this type of algorithm). Briefly, the calculation divides the entire country into cells, and the cost to travel over each cell in the grid depends on whether it contains a segment of road (paved or unpaved), railroad, navigable river or no transportation mode. To assign the travel costs for each transportation mode, I use the freight rate data collected by SIFRECA. I adjust for road quality in the calculations using the Vehicle Cost Module of the World Bank's Highway Design Model (HDM-VOC-4), which is designed to calculate unit road user costs for different types of road sections. The optimization routine in ArcGIS determines the least cumulative cost path from each origin to the nearest destination. Because almost all the information I obtained from SIFRECA for the Amazon corresponds to costs of transporting soybeans, the proxy TC_m measures the minimum cost of transporting 1 ton of soybeans.

5.3 Summary Statistics

There are 523 municipalities in the data set. Table 1 presents summary statistics. Farms occupy almost 40 percent of the municipal area on average; and the average fraction of private land used for agriculture is 65 percent. The cost to transport 1 ton of soybean from the South Amazon (the region where the soybean is primarily grown) to the Port of Santos is 30 percent of the price of soybeans at the port – a significant cost for farmers. As expected, high levels of temperature and rainfall are prevalent, and most of the soil is of poor quality for agriculture. The average number of fines per municipality increased steadily over the period 2002–2006, consistent with the numbers provided in Subsection 3.4 (i.e., the small proportion of deforested areas that received fines) given the high levels of deforestation before 2006. The average difference between the carbon stock in forested and deforested areas is approximately 80 tons of carbon per hectare.

Table 2 provides information about the different farm sizes. The numbers in the cells are sample

Table 1: Summary Statistics

Variables	Mean	Std Dev	Min	Max
Land Use				
Number of Farms per Municipality	1225	1169	37	11544
Share of Farm Area on Municipal Area	0.39	0.27	0	0.98
Share of Deforestation on Private Area	0.65	0.2	0.12	1
Transportation Costs				
Cost to Port (US$/ton)	41.4	33.5	0	163
Distance to Port (km)	866	717	0	2627
Distance to Capital (km)	314	218	0	900
Agro-Climatic Variables				
Temperature (^{o}C/year)	26.5	0.56	25	27.5
Rainfall (mm/year)	184	32	116	272
Altitude (meters)	118	126	0	920
Slope (degrees)	0.54	0.39	0.03	3.03
Share of Good Soil	0.05	0.17	0	0.99
Share of Good/Medium-Quality Soil	0.08	0.22	0	1
Share of Medium-Quality Soil	0.04	0.18	0	0.99
Share of Low-Quality Soil	0.51	0.38	0	1
Share of Unsuitable Soil	0.31	0.35	0	1
Local Demand-Supply Shifters				
Number of Local Mines	0.81	2	0	22
Number of Local Power Plants	0.04	0.2	0	1
Local Population (thousands)	31	96.4	1.92	1405
Monitoring				
Number of Fines in 2002	2.01	4.84	0	41
Number of Fines in 2003	5.56	15.7	0	226
Number of Fines in 2004	7.45	25.2	0	449
Number of Fines in 2005	7.85	18.1	0	192
Number of Fines in 2006	10.7	23.8	0	178
Cumulative Number of Fines 2002–2005	23	54.6	0	735
Distance to IBAMA (km)	74.8	56.4	0	303
Other Variables				
Distance to Protected Areas (km)	40.2	32.4	0	167.7
Share of Land with Land Title	0.93	0.12	0.01	1
Carbon Stock				
Carbon Stock in Forested Areas (tC/ha)	188.6	68.25	49	339.6
Carbon Stock in Deforested Areas (tC/ha)	108.8	41.52	9.48	246.3

Notes: The unit of observation is a municipality in the Amazon.
There are 523 municipalities in the data.
Source: Author's calculations.

averages across municipalities. The concentration of land is clear from the table: despite the fact that large farms are a small proportion of the total number of farms (5 percent), they occupy about 50 percent of the private farmland, while small farms account for 21 percent of the farms and occupy only 1 percent of the private land. The small landholders tend to deforest a large part of their land (90 percent), but the proportion of deforestation diminishes as farm size increases. Recall that the existing legislation requires the deforestation to be less than 20 percent of the property.

Table 2: Summary Statistics by Farm Sizes (Sample Averages)

Statistics	Small	Small–Medium	Medium–Large	Large
Number of Farms per Municipality	302	414	353	46
Share of the Number of Farms	0.21	0.33	0.31	0.05
Share of the Private Area	0.01	0.11	0.38	0.5
Share of Agriculture on Private Area	0.90	0.71	0.69	0.63
Local Yields (q_m)	0.70	0.42	0.41	0.27
Number of Municipalities	501	520	520	450

Notes: The unit of observation is a municipality in the Amazon.
The numbers in the cells are sample averages across municipalities.
Source: Author's calculations.

6 Effects of Transportation Cost on Deforestation

This section presents the estimated impact of transportation costs on deforestation. I first check for the presence of weak instruments, then I turn to the land-use regressions. I leave the results of the semiparametric quantile IV model for the Supplemental Material because there are no significant differences between the logit and the semiparametric models. This fact suggests that the quantile logit model is sufficiently flexible for the current data set.

6.1 First Stage Regression

Table 3 presents the results from regressing transportation costs to the nearest port on straight-line distances. For brevity, the estimated coefficients on the other covariates are omitted. It is clear that both straight-line distances to ports and to the nearest capital are strong predictors of costs to ports and that there is no issue with weak instruments in this data set. Increasing the distance to the nearest port by 100 km raises the cost to transport 1 ton of soybeans by US$ 4 on average (which corresponds to 10 percent of the average transportation cost – see Table 1).

Table 3: First Stage Regression

	Costs to Port
Distance to Port	0.041***
	(29.08)
Distance to Capital	0.012***
	(4.86)
Observations	523
F-statistic	862.39
R^2	0.92

t-statistics in parentheses, *** $p < 0.001$.

6.2 Land Use Regressions

Next, I present results for the logit models. Table 4 reports the estimated coefficients for costs to the nearest port and the associated t-statistics in parentheses for the OLS, 2SLS, quantile regression (QR), and the instrumental variable quantile regression (IVQR) for each farm size. The coefficients on the other regressors are omitted in the table, but they are reported in the Supplemental Material, where I discuss several robustness exercises.[39]

I begin by comparing the OLS and the 2SLS estimates. Recall that the typical exercise in the literature uses OLS to estimate the land-use regressions. As discussed in Subsection 4.2, it is not clear *ex-ante* what the direction and magnitude of any bias from the OLS estimates would be. The OLS coefficients in Table 4 are small in magnitude and are not significantly different from zero. In addition, they predict positive impacts of costs to ports on the share of agricultural land for small and medium-sized farms. When transportation costs are instrumented for using straight-line distances, the coefficients increase in magnitude (except for smallholders) and their signs become negative for all farm sizes. Similarly to OLS estimates, however, the 2SLS coefficients are also imprecisely estimated.

Next I focus on the quantile regressions. The IVQR coefficients for medium-sized and large farms are negative, and almost all are significant and greater in absolute value than the QR coefficients. The coefficients differ across quantiles, so even after controlling for observable municipality-level variables, farms with different levels of deforestation appear to respond differently to changes in transportation costs.

The heterogeneity in responses across quantiles can be illustrated graphically. Figure 3 presents

[39] For all farm sizes, the overidentification tests fail to reject the null of valid instruments. For small farms, the test statistic is 0.93 (p-value = 0.33); for small–medium, 1.01 (p-value = 0.31); for medium–large 1.81 (p-value = 0.18); and for large farms, 0.73 (p-value = 0.39). Inference for the quantile regressions are based on the results of Chernozhukov and Hansen (2008). Currently, there exists no estimation method that incorporates spatial correlation in the unobservables into quantile regressions.

Table 4: Land-use Regression Model by Farm Size – Coefficients on Costs to Ports

	OLS	2SLS	Quantiles				
			10	25	50	75	90
Small							
No IV	0.0116	-	0.0098**	0.0080*	0.0110**	0.0080	0.0185
	(1.44)	-	(2.24)	(1.75)	(2.10)	(1.18)	(1.20)
IV	-	-0.0024	0.0080*	0.0027	0.0045	-0.0003	-0.0121
	-	(-0.27)	(1.80)	(0.55)	(0.76)	(-0.03)	(0.48)
Small–Medium							
No IV	0.0022	-	-0.0034	0.0008	-0.0025	-0.0018	0.0078
	(0.45)	-	(-1.08)	(0.24)	(-0.81)	(-0.48)	(1.08)
IV	-	-0.0063	-0.0049	-0.0023	-0.0053	-0.0063*	-0.0008
	-	(-1.20)	(-1.41)	(-0.65)	(-1.58)	(-1.66)	(-0.11)
Medium–Large							
No IV	0.0040	-	-0.0101***	-0.0085**	-0.0025	0.0034	0.0110**
	(1.04)	-	(-3.03)	(-2.49)	(-0.73)	(0.95)	(2.19)
IV	-	-0.0058	-0.0184***	-0.0112***	-0.0079**	-0.0042	-0.0010
	-	(-1.50)	(-4.78)	(-3.03)	(-2.07)	(-1.06)	(-0.21)
Large							
No IV	-0.0023	-	-0.0113***	-0.0102***	-0.0077**	-0.0063	-0.0084
	(-0.49)	-	(-2.81)	(-2.62)	(-2.03)	(-1.41)	(-1.56)
IV	-	-0.0077	-0.0110***	-0.0109***	-0.0110***	-0.0107**	-0.0156***
	-	(1.33)	(-2.58)	(-2.69)	(-2.91)	(-2.53)	(-3.15)

Notes: This table reports the estimated coefficients on transportation costs based on the OLS, 2SLS, QR, and IVQR estimators. For each farm size, the dependent variable is the log odds ratio of the share of deforestation. The unit of observation is a municipality in the Amazon. The number of observations for small farms is 501, for small-medium farms is 520, for medium–large farms is 520, and for large farms is 450.
t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

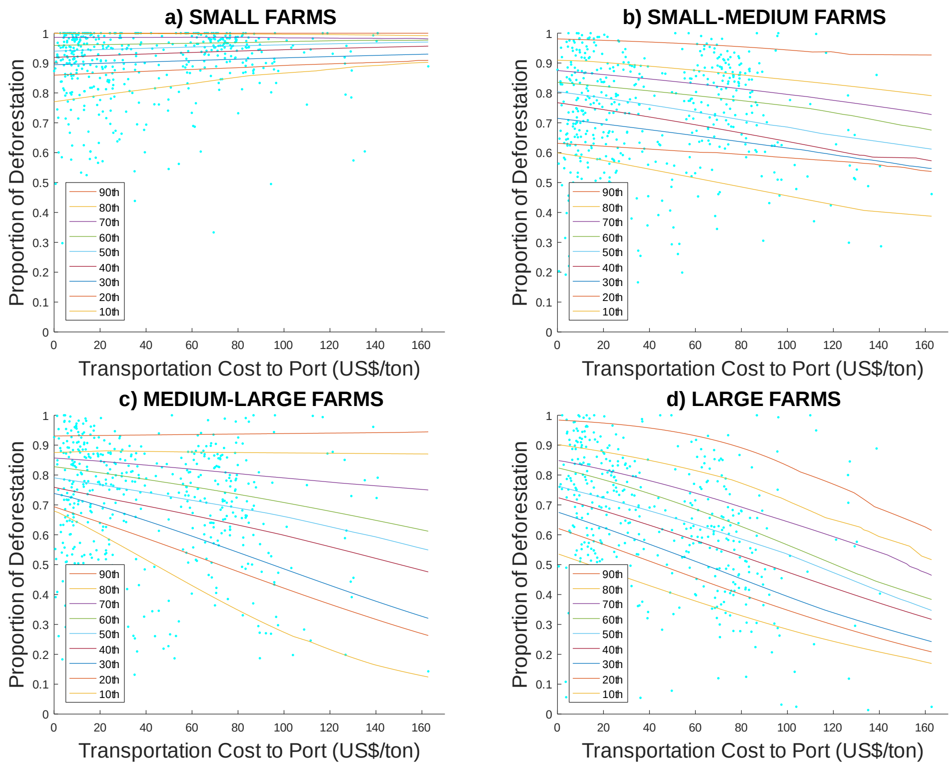

Figure 3: Quantile Functions – Share of Deforestation vs. Costs to Ports

the data and the curves for the deciles $u = 0.1, 0.2, ..., 0.9$ obtained from estimating the IVQR. The regressors are fixed at the sample average and costs to ports vary over the observed range in the data. It is clear that small landholders are insensitive to transportation costs – almost all of their IVQR coefficients are not significantly different from zero and the lines in panel (a) are flat for all but the lowest decile. This seems reasonable because small farms tend to be concentrated in isolated regions in the Western Amazon and produce manioc, which is consumed domestically and does not require a significant amount of inputs. They are most likely producing for subsistence and are not engaged in the market. As such, their decision to deforest must be driven by the shadow value of food, and not by the costs to the nearest port. Even though they likely respond to payment programs or to land use taxes, the econometric model does not seem to be well-suited for them and so my strategy most likely fails to identify their demand for deforestation. Despite these problems, the behavior of small landholders does not play a major role in environmental policies given that they occupy only 1 percent of the private land.

For other farm sizes, the upper-tail quantile curves tend to be concave, while the lower-tail quantile curves tend to be convex, which conforms to the discussion in Subsection 4.1. These results reveal that the mean effects estimates based on 2SLS mask considerable heterogeneity. The heterogeneity in responses, according to the IVQR estimates, can vary substantially across (a) farm sizes s, (b) quantiles u (for any given s and TC), and (c) transportation costs (for any s and u).[40]

Table 5: Marginal Effects of Costs to Ports by Farm Size

	Quantiles				
	10	25	50	75	90
Small					
Share of Deforestation (%)	76.89	87.57	94.24	98.66	99.99
Marginal Effect	1.421	0.297	0.245	-0.004	-0.001
Small–Medium					
Share of Deforestation (%)	49.99	61.54	74.17	85.02	93.29
Marginal Effect	-1.230	-0.543	-1.020	-0.808	-0.047
Medium–Large					
Share of Deforestation (%)	46.64	58.87	72.13	83.41	90.80
Marginal Effect	-4.575	-2.719	-1.580	-0.585	-0.086
Large					
Share of Deforestation (%)	38.80	50.64	65.18	77.99	89.53
Marginal Effect	-2.605	-2.713	-2.505	-1.837	-1.466

Notes: This table reports the estimated shares of deforestation based on the IVQR model presented in Table 4, holding covariates at the sample mean. It also shows the estimated marginal effects of transportation costs on the share of deforestation based on the IVQR model. Marginal effects are measured in percentage points and correspond to an increase of \$10 per ton in transportation costs.

To have a sense of the magnitudes involved, Table 5 presents the estimated marginal effects of transportation costs on the share of deforestation for each farm size and for different quantiles based on the IVQR model. The marginal effects are measured in percentage points and correspond to an increase in transportation costs of \$10/ton, which is approximately one third of a standard deviation in the data – see Table 1. The covariates are fixed at the sample average. Consistent with Figure 3, the marginal effects tend to be greater at lower quantiles and for larger farms. Taking

[40] To compute the curves in the figure, I rearranged the quantiles for each point in the data following the procedure proposed by Chernozhukov, Fernández-Val, and Galichon (2010) to avoid quantile crossing. The model is estimated for quantiles ranging over $\{0.05, 0.1, ..., 0.95\}$ to avoid problems with extreme quantiles.

the (conditional) median, note that, while increasing transportation costs by $10/ton increases the estimated fraction of deforestation on small farms by only 0.24 percentage point, it reduces the corresponding fraction of deforestation on medium-sized farms by 1-1.5 percentage points, and on large farms by 2.5 percentage points.

7 Demand for Deforestation

In this section, I present and discuss the estimated demand for deforestation on private properties. I also assess the geographic distribution of demand. I then investigate how the demand changes when I hold the total number of fines after 2004 at pre-2004 levels to separate the effects of taxes from the increased government monitoring efforts observed after 2004.

To compute the demand function, I use the IVQR estimates of the logit model together with equation (3) in Section 4 to predict the fraction of agricultural land on private properties for each hypothetical tax, for each farm size, and for each municipality in the data set.[41] Then, for each tax, I compute the total deforested area from the predicted share of agricultural land. By summing over municipalities, I obtain the corresponding demand for each farm size. Finally, the total demand is obtained by summing over the farm sizes.[42]

Figure 4 presents the demand for deforestation for each farm size and the total demand function. One may interpret the total demand in the following way: if the government had increased the relative value of the forested land by imposing a perfectly-enforced tax that charged, say, US$ 42.5/ha of agricultural land per year, farmers would be willing to use approximately 15.5 million hectares for agriculture (20 percent of the private properties) instead of the actual 43.2 million hectares (56 percent). Because farmers' average gross revenue per hectare in the Amazon in 2006 was US$ 120/ha, such a tax would drive many farmers out of production.[43]

It is clear from Figure 4 that the shape of the total demand mainly comes from the demand of large farms. The extremely unequal distribution of land in the Amazon coupled with the response of large farms to taxes suggest that policies targeting *only* small landholders cannot promote significant

[41] In practice, I impose the rank invariance condition in the following way: for each farm size s and each municipality m, I compute the estimated QTR function $X_m'\beta_s(u) - \alpha_s(u) \times TC_m$ for all quantiles. I then rearrange the quantiles according to the procedure proposed by Chernozhukov, Fernández-Val, and Galichon (2010) to avoid quantile crossing. The rank u associated with observation (s, m) is the one that minimizes the difference between the observed $\log(Y_m(s) / (1 - Y_m(s)))$ and the estimated QTR function. I hold the rank fixed when calculating the demand for deforestation.

[42] An implicit assumption in this calculation is that taxes would not change the distribution of farm sizes. Although taxes could affect the sizes of farms, such impacts are beyond the scope of the paper (see a discussion of this point in Subsection 8.3).

[43] One may interpret the results in terms of expected taxes that farmers would pay instead of a perfectly enforced tax.

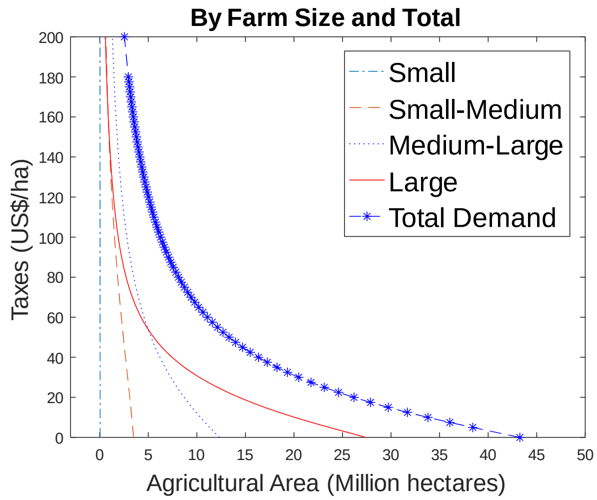

Figure 4: Demand for Deforestation

conservation (recall that they occupy only a small fraction of the total land – see Section 5.3). Although taxes or payments can be effective in changing small farmers' behavior (see Simonet *et al.* (2015) for a recent small-scale PES program in Pará State), it is evident that payments are unlikely to substantially reduce local poverty and deforestation simultaneously. This result is consistent with the analysis by Godar *et al.* (2014), who document that most of the deforestation in the Amazon between 2004 and 2011 occurred in regions dominated by large farms (those with more than 500 hectares).

7.1 Geographic Distribution

In Figure 5, I present the geographic distribution of the counterfactual deforestation. The top left panel presents the total agricultural area computed from Census data – the darker the region, the larger the area occupied by agricultural land. The top right panel presents the counterfactual agricultural land for taxes of US$ 20/ha; the bottom left, the corresponding map for taxes of US$ 40/ha; and the bottom right panel gives the map for the US$ 100/ha tax. By comparing the top-left map (no tax) with, say, the top-right map (US$ 20/ha tax), it is possible to see which regions are mostly affected by the US$ 20/ha land-use tax.[44]

The figure makes clear that farmers in the 'Arc of Deforestation' respond less to taxes. Even under a tax of US$ 100/ha, farmers in the South Amazon, the region where the soybean is produced, would be willing to use their land intensively. The opportunity costs of the agricultural area in this region are probably too high to not be used for agriculture. In contrast, forests in the central and

[44] The numbers in the legend correspond to the quantiles of the agricultural area in the data, and are the same for all maps. The quantiles are $\{0.01, 0.05, 0.1, 0.2, 0.3, ..., 0.8, 0.9\}$.

western regions can be preserved more under taxes and so be less fragmented, which is advantageous from a biodiversity point of view.

[FIGURE 5 HERE]

7.2 Monitoring Efforts Post-2004

As discussed in Section 3, government monitoring increased after 2004, mostly through the use of satellite-based monitoring systems. In order to try to separate the effects of taxes from the recent monitoring innovations, I compute the demand for deforestation holding the total number of fines issued during the 2004–2005 period at the same level as the number of fines issued during the previous period (available in the data), 2002–2003. This reduces the cumulative number of fines from an average of 23 fines per municipality to 15 (and it reduces the standard deviation as well, from 55 to 39). In doing so, I "shut down" the recent increase in monitoring effort in the estimated demand for deforestation.

Figure 6 presents the two demand functions. Eliminating the recent increase in monitoring amounts to an upward shift in deforestation levels, as expected. But the differences are economically small. In the absence of land-use taxes, the share of deforested area increases by 3 percentage points, from 56.2 percent to 59.3 percent on the private properties. The two demand curves are close to each other throughout. Even though the use of satellite-based monitoring is an important innovation that likely has large effects on deforestation in the long run (see, e.g., Assunção, Gandour, and Rocha (2013)), it appears too recent to affect the demand function in 2006 substantially.

[FIGURE 6 HERE]

8 Policy Analysis

In this section, I apply the framework to examine important policy questions. First, I consider the implications for carbon emissions and for the optimal tax. I then examine the resulting economic costs for the three policy interventions (taxes, payments and the '80 percent rule'). I close the section with a discussion of the limitations of the analysis.

8.1 Emissions of CO_2 and Optimal Tax

Avoided Emissions. To derive implications for emissions of carbon, estimates of the carbon stock in forested and deforested areas are required. Baccini *et al.* (2012) recently measured the geographic distribution of the aboveground carbon stock in Brazil. I combine their map of the carbon stock with the maps of deforestation from satellite images (INPE (2017)) and compute, for each municipality, the difference in the carbon stock in forested and deforested areas. These may vary across municipalities because forests are heterogeneous and the alternative land uses in agriculture may conserve more or less carbon on the ground. The average difference is almost 80 tons of carbon per hectare (tC/ha) – see Table 1.

Combining the differences in carbon stocks with the demand for deforestation results in a 'supply of avoided emissions.' Figure 7 presents this supply function. One may interpret the curve in the following way: if a carbon tax of (or a payment program paying) US$ 1 per ton of CO_2 per year were implemented, farmers would be willing to avoid the emissions of approximately 4.17 billion tons of carbon. The avoided emissions correspond to approximately 4.5 years of worldwide emissions from land use change during 2002 to 2011 (IPCC (2013)). The flat part of the curve is the result of the large stocks of carbon in forested areas combined with the fact that farmers would be responsive to taxes. The steeper portion, to the right, is the result of capacity constraints: with higher taxes, farmers would be willing to keep almost all the total private land forested.[45]

The shape of the supply curve I estimate is similar to other studies; see, e.g., Nepstad *et al.* (2007). Kindermann *et al.* (2008) and Lubowski and Rose (2013) also investigate the costs of avoided emissions from deforestation based on a number of different large-scale models (most of which are 'engineering/costing' models). Although comparing my results to this literature is not trivial (because the approaches differ in several dimensions – the modelling assumptions, the underlying data, the spatial resolution, the region and time period covered, and the baseline deforestation rate in the absence of carbon taxes/payments, among others), the results indicate the significant potential for emissions reduction through reducing deforestation, which can play an important role in global climate change policies.

A carbon tax of US$ $1/tCO_2$ per year is significantly smaller than the average price of carbon in the European Union Emissions Trading System. The carbon price was US$ $8.5/tCO_2$ in December of 2006, and US$ $5.8/tCO_2$ (2006$) ten years later.[46] The difference between the potential carbon tax and the market price of carbon suggests substantial opportunities for trade, but such oppor-

[45]The calculation assumes that (a) the difference in the carbon stock comparing forested and deforested areas would be released into the atmosphere once the forest was removed (i.e., it ignores the decay rate); and (b) the carbon taxes would not affect the amount of carbon stock in agricultural land, although, in principle, farmers could respond to carbon taxes by using new techniques that conserve more carbon on the ground. To better understand the calculation, note that for a parcel in which the carbon difference between forested and deforested land is 80 tC, a land-use tax of \$10/ha is equivalent to a carbon tax of \$0.125/tC (and to $\$0.034/tCO_2$, because $1tC = 44/12\ tCO_2$).

[46]The calculation converts dollars to 2006 using US Consumer Price Index data.

tunities have not yet been realized. One possible reason lies in the potentially large transactions costs involved. Measuring and monitoring the amount of carbon stocks may be expensive. Perhaps more importantly, measuring avoided emissions depends on the counterfactual emissions that would occur in the absence of payments, which is not trivial to compute.

[FIGURE 7 HERE]

Optimal Tax. The value of a Pigouvian tax is the marginal damage of the externalities caused by deforestation, such as emissions of carbon and biodiversity loss, at the social optimum. Because it is difficult to measure the production of all the relevant externalities and to value the corresponding damages, I focus on a lower bound for the optimal tax, which can be obtained from the estimated damages associated with an incremental change in CO_2 emissions. According to Greenstone, Kopits, and Wolverton (2013), the central value of the social cost of carbon (SCC) for 2010 was US$ 20.4/tCO_2 (2006$). Nordhaus (2014) estimates the central value of the SCC for 2015 to be US$ 19.1/tCO_2 (2006$). As Figure 7 shows, imposing taxes of this magnitude would virtually eliminate all agricultural land in the Amazon.

The Amazon is responsible for 20 percent of Brazil's agricultural area. If no land in the Amazon were used for agriculture, one would expect non-trivial impacts on the national economy, on Brazil's trade balance, and possibly on the international prices of beef and soybeans. Increases in the prices of these products could diminish the welfare from the consumption of food. The present paper does not take these effects into account.

8.2 The Costs of the Policy Interventions

Brazil adopted a command-and-control policy approach that obligates farmers in the Amazon to keep 80 percent of their land in the form of native forest. I calculate a lower bound for the hidden cost of this policy by means of a perfectly-enforced land-use tax that induces farmers to use only 20 percent of their properties for agriculture. I compute this tax for each municipality and for each farm size (which is the most disaggregated information available in the data set). The corresponding farmers' lost surplus from these taxes is the sum of the trapezoid areas below each demand curve. The sum amounts to US$ 4.41 billion. Farmers are therefore estimated to be willing to pay US$ 4.41 billion per year to avoid the enforcement of the 80 percent rule. Not surprisingly, farmers have tried systematically to alter the legislation since its implementation.[47]

[47] In actuality, the amount of money they would be willing to pay is likely even larger, for three reasons: (a) the command-and-control policy imposes the same limit on farmers' land use regardless of the differences in opportunity

A uniform tax charging US$ 42.5/ha per year of agricultural land would also lead to 20 percent of land used for agriculture, but it would have been almost ten times cheaper than the '80 percent rule': farmers' lost surplus would be approximately US$ 479 million per year, provided the tax revenues were redistributed to them (tax revenues would be approximately US$ 658 million per year, which is 0.37 percent of the Brazilian federal budget for 2006). The difference corresponds to a cost saving from the land use tax of approximately 90 percent of the cost of a perfectly enforced '80 percent rule.' This is substantially higher than the cost saving estimates from allowance trading in pollution markets when compared to standard caps on emissions, which range from 20 to 47 percent (see Schmalensee and Stavins (2017) and the literature cited therein). The '80 percent rule' is not a cost-effective policy: the more productive farms would have to use less land for agriculture and so would have foregone more profits, compared to taxes. Although in theory command-and-control approaches could also be cost-effective, they would require policy makers to obtain detailed information about each farmer's opportunity costs of land use, and set different limits on land use for each farm. Such information is not readily available to policy makers (Stavins (2000)).[48]

To cover other possible policy responses, I now briefly discuss payment programs. Similar to taxes, payments of US$ 42.5/ha would also result in 80 percent of forest cover, and lead to the same economic costs: US$ 479 million per year. Total transfers to farmers (potentially from the federal government) would have been US$ 2.61 billion per year (1.45 percent of the Brazilian federal budget for 2006). A perfectly targeted policy paying farmers who were going to deforest, but *not* paying those who were *not* going to deforest, would reduce total transfers by more than a half (US$ 1.18 billion per year). Perfect targeting is unlikely, however, because of asymmetric information problems (see Pattanayak, Wunder and Ferraro (2010), Busch *et al.* (2012), and Mason and Platinga (2013)).[49]

As noted previously, the 2SLS estimator cannot capture heterogeneous responses to changes in private values, and this may affect the estimated costs of policy interventions. Indeed, the 2SLS parameter estimates presented in Table 4 are relatively small in magnitude and fail to capture the high sensitivity of deforestation to changes in transportation costs at some quantiles. As a

costs of agricultural land, while the local land-use taxes I used to approximate the '80 percent rule' are (locally) a cost-effective price instrument; (b) the legislation does not allow for managed forests in preservation areas, except under very stringent conditions, but the forested area in the data potentially includes managed forests; and (c) the costs to replant the vegetation add to the farmers' total costs since, by law, they must restore the forest at their own expense.

[48] Quantitative limits could be combined with trading, which would improve efficiency; see May *et al.* (2015) for an excellent discussion of environmental quotas to conserve or restore forests.

[49] Busch *et al.* (2012) find that a REDD+ program in Indonesia paying local agents uniformly would result in excessive payments for some participants while providing insufficient incentives to others. It would also result in budgetary losses.

consequence, the land-use tax that results in there being 80 percent forest cover and that is based on the 2SLS estimates would be substantially higher: US$ 65/ha. The corresponding economic cost would be approximately US$ 786 million, which is 64 percent higher than the estimated cost based on the quantile approach. The greater lost surplus from the 2SLS estimator points to the importance of allowing for heterogeneity in the demand for deforestation.

8.3 Limitations

The above analysis has some limitations that I discuss next. First, the estimated economic costs of the policies do not take into account monitoring and transactions costs. Given that Brazil does not yet have an established system to monitor the public expenditures directed to environmental issues (OECD (2016)), a useful proxy for existing monitoring costs is the sum of INPE's and IBAMA's combined annual budgets.[50] These combined budgets are likely to provide an upper bound on the monitoring costs, since not all resources are directed to monitoring. INPE's budget for 2010 was US$ 125 million, and IBAMA's budget for 2011 was US$ 560 million. These numbers are comparable to the US$ 658 million of government tax revenues I obtained under a land-use tax of US$ 42.5/ha. This suggests that tax revenues could be sufficiently large to cover monitoring and enforcement costs.

A second limitation is that indirect effects are not considered here.[51] For instance, I have not estimated by how much the total private land (and the land distribution) would respond to the policies. Although such an exercise is possible, there are important implications that cannot be addressed with the present data set. For example, the '80 percent rule,' if perfectly enforced, may provide incentives to have large farms. Also, plenty of unprotected public forested land might be occupied in response to payment programs. Such occupations might reduce the potential effectiveness of the programs, increase their total costs, and increase disputes over land along with the potential violence associated with these disputes. The results I present should thus be viewed as one of the inputs necessary for a complete evaluation of conservation policies.

9 Conclusion

In this paper, I have set out a unified econometric framework to estimate the impacts and cost effectiveness of alternative conservation policies. Applied to the Brazilian Amazon, the main pol-

[50] INPE is responsible for the detection of 'hot spots' using satellite data and for providing the information to IBAMA. IBAMA then sends their inspectors to those hot spots, issues the appropriate fines, and follows up with the administrative and judicial processes.

[51] See Lubowski and Rose (2013) for a discussion of commodity market feedbacks associated with REDD+ programs.

icy implications of this exercise are the following: (a) land-use taxes and payment programs can be effective in avoiding deforestation and the emissions of carbon; (b) policy interventions that *only* target the small landholders are not sufficient to promote substantial conservation; and (c) command-and-control policies that limit deforestation allowed on private properties are considerably more costly than incentive-based policies.

There are several directions for future research. First, accessing micro-data on farmers' decisions is likely to provide a fuller picture of their opportunity costs and avoid the potential drawbacks of using aggregated measures for local yields. Furthermore, micro-data may reveal the entire distribution of farmer's private valuations within each municipality, which may help address issues such as the use of auctions to allocate PES contracts. Second, a panel data set based on satellite images would allow a dynamic model of land use decisions to be estimated. Such a model could be used to study impacts of commodity prices on the rate of deforestation and how much these prices could affect the effectiveness of different policy interventions. Third, the framework presented here can be used to study impacts of improvements of roads on deforestation. This is an important topic, looking ahead, because the Brazilian government is paving some unpaved roads in the Amazon to reduce the costs of exporting commodities.

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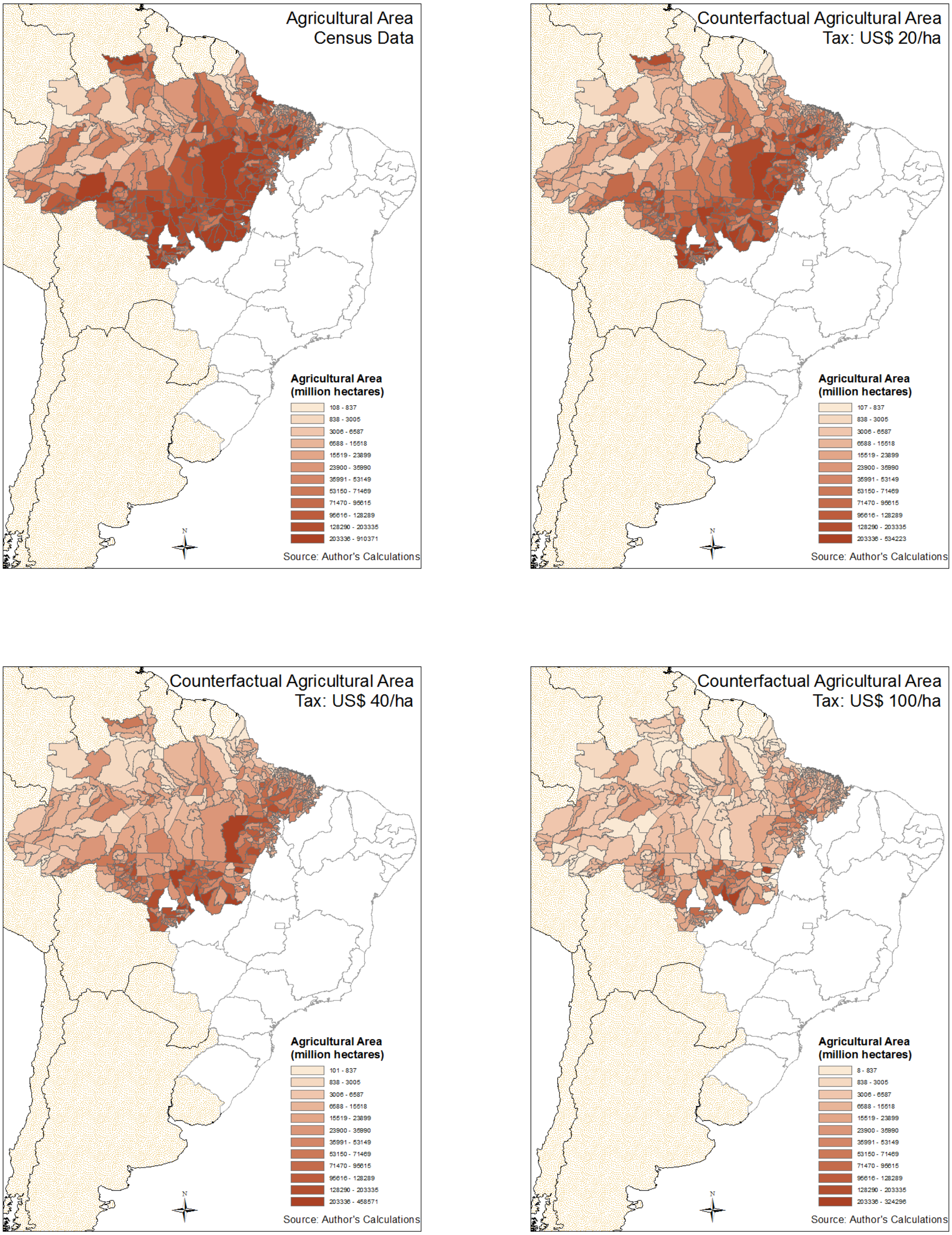

Figure 5: Geographic Distribution of the Demand for Deforestation

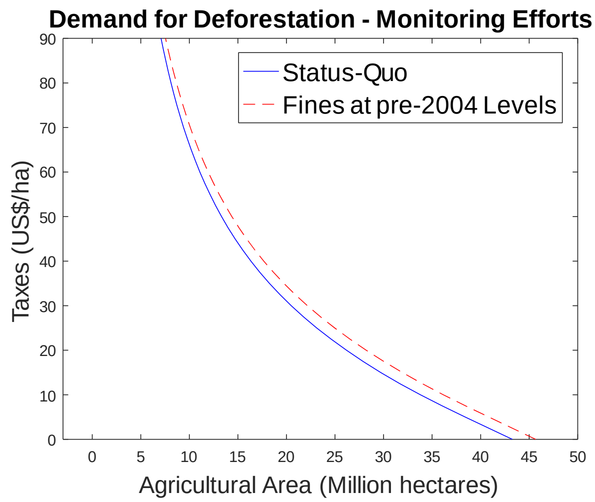

Figure 6: Demand for Deforestation – Eliminate Increases in Monitoring after 2004

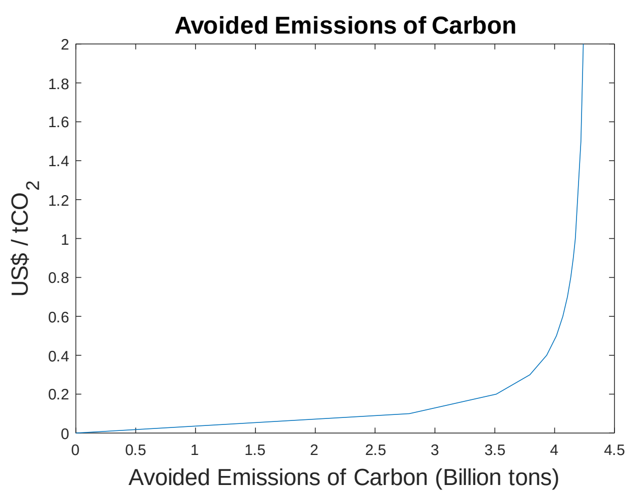

Figure 7: Supply of Avoided Emissions of Carbon