Journal of Environmental Economics and Management 108 (2021) 102452

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Commodity prices and robust environmental regulation: Evidence from deforestation in Brazil☆

Torfinn Harding [a,b,*], Julika Herzberg [c], Karlygash Kuralbayeva [d]

[a] *University of Stavanger, Norway*
[b] *NHH Norwegian School of Economics, Norway*
[c] *RWTH Aachen University, Germany*
[d] *King's College London, UK*

ARTICLE INFO

Article history:
Received 8 March 2019
Revised 6 April 2021
Accepted 8 April 2021
Available online 26 April 2021

JEL classification:
O13
Q15
Q17
Q28
Q54

Keywords:
Deforestation
Commodity prices
Protected areas
Soy moratorium
Priority municipalities
Environmental regulation
Climate change

ABSTRACT

Increasing international agricultural commodity prices create pressure on tropical forests. We study the effectiveness of three regulatory policies implemented by Brazil in reducing this pressure: *blacklisting* of municipalities, the *Soy Moratorium*, and *conservation zones*. We use a triple difference approach that combines international agricultural commodity prices with the policies across three million km^2 in the Brazilian Amazon. We find that the blacklisting program is effective, as it reduces deforestation related to the prices by 40%. The Soy Moratorium made deforestation in exposed municipalities more sensitive to non-soy prices, in line with crop substitution. Conservation zones amplify the effect of prices on deforestation on the remaining unprotected land, consistent with reduced land supply. Our results highlight that the effect of environmental regulation depends on the economic pressure to use natural resources.

1. Introduction

Land-use change, largely due to tropical deforestation (Mitchard, 2018), is estimated to account for about 10–12% of anthropogenic CO_2 emissions in the years 2000–2015 (Le Quéré et al., 2016; Edenhofer et al., 2014). The backdrop of high deforestation

☆ We would like to thank Lassi Ahlvik, Alexis Rivera Ballesteros, James Cust, Nicolas Koch, Oliver Lorz, Michael Ross, Henrik Sigstad and Po Yin Wong, participants of the Natural Resource and Governance Workshop 2017 at NHH (Bergen), BEEER 2017 (Bergen), WCERE 2018 (Gothenburg), seminar participants at LSE, NHH, Statistics Norway, University of Helsinki and University of Oslo as well as two anonymous referees and the editor for helpful comments and discussions. We are also grateful to Juliano Assunção, Clarissa Gandour, Romero Rocha and Rudi Rocha for sharing with us their data on rural credit and fines. We thank Liana Anderson, Bruna Pechini Bento, Andre Lima, Ana Carolina Pessoa and Sacha Siani for discussions and preparation of various forest and policy data. We thank The TREES lab and Luiz Aragao for their hospitality. The project was financed by the Research Council of Norway (project 230860). Support from the Equinor Chair in Economics at NHH is also gratefully acknowledged.

* Corresponding author. University of Stavanger, Norway.
E-mail addresses: torfinn.harding@uis.no (T. Harding), julika.herzberg@rwth-aachen.de (J. Herzberg), karlygash.kuralbayeva@kcl.ac.uk (K. Kuralbayeva).

https://doi.org/10.1016/j.jeem.2021.102452

rates has been strong global economic growth, high global energy prices, subsidies for biofuels and a doubling of the real price of agricultural commodities like grains (Mitchell, 2008; Alexandratos, 2008). Large scale agriculture accounted for about two-thirds of deforestation in Latin America and one-third in Africa and Asia in the period 2000–2012 (Kissinger et al., 2012). Around half of such deforestation can again be attributed to the cultivation of crops for export markets like the EU, China and North America (Lawson, 2014). In response, countries such as Brazil have committed to an array of command and control and market-based policies to reduce deforestation. The question addressed in this paper is whether such policies are effective in curbing deforestation related to higher commodity prices.

We evaluate the effectiveness of three central policy measures implemented in Brazil. The policies vary in terms of the deforestation they target. *Blacklisting of municipalities* (PM) targets municipalities with high deforestation rates by the means of increased monitoring and law enforcement as well as by more stringent conditions for subsidized rural credit.[1] This policy focuses on the total extent of deforestation at the municipality level. The *Soy Moratorium* (SM) is an industry-driven initiative that aims to keep the commodity supply chain clean of soybeans that come from recently deforested land. Hence it focuses on deforestation caused by soy cultivation. *Conservation zones* (CZ) impose regulation on certain geographic areas. In this paper, we include three broad categories of protected areas in what we call Conservation Zones, namely indigenous lands, sustainable use conservations zones and strictly protected conservations zones. We study the deforestation frontier in the Brazilian Legal Amazon. This is the part of the Amazon, the largest forest left on earth, that is likely to have experienced the most intense deforestation pressure to date. Our main dataset is a balanced panel of 470 municipalities covering the years 2002–2013 and about three million km^2. The main analysis focuses on deforestation outside of the protected areas.

We begin our analysis by estimating the direct effect of agricultural commodity prices on deforestation. We construct a municipality-level price index based on international real prices. We use weights based on each municipality's cultivated area of the different crops in 2002, the initial year of our sample. Consistent with the finding of Hargrave and Kis-Katos (2013), we find that higher agricultural commodity prices are associated with higher deforestation. We estimate that a 100% increase in the prices leads to an increase in deforestation of about 40%. The average 56% higher level of the price index over 2004–2013 compared to 2003 then contributes with 1,700 km^2 of additional deforestation each year. This adds up to about 19% of the total deforestation of 91,000 km^2 in our sample over the ten-year period 2004–2013.

Next, we estimate how the effect of international agricultural commodity prices varies with the policies, which represents the main contribution of the paper. We use the municipality-specific index of prices interacted with policy exposure in a triple difference model (DDD). This model essentially compares price effects in municipalities exposed to a given policy with price effects in municipalities not exposed to the policy. Exposure to a policy varies both across municipalities and over time. We cannot reject common differential trends in deforestation in the pre-policy period, suggesting that our design effectively nets out potentially confounding factors driving both deforestation and the policy-roll out.

We find that the policy of *blacklisting* municipalities reduced the impact of commodity prices on deforestation by about 40%, saving 35 km^2 forest per treated municipality per year. In our sample, the total saved forest due to this effect is 9,000 km^2. This is consistent with the expected effect that the policy increases the costs of deforestation. Previous studies have also suggested that this policy reduced deforestation.[2]

For the *Soy Moratorium*, we do not find a robust statistically significant effect for the agricultural commodity price index. This overall ineffectiveness masks two effects working in opposite directions: the soy price has a lower effect on deforestation under the Soy Moratorium, while the prices of other crops have a higher effect. This is consistent with the Soy Moratorium reducing deforestation related to soy cultivation, while the production of alternative crops is moved to or expanded on newly deforested areas. Corn may be a case in point. We find deforestation to be more sensitive to the price of corn due to the Soy Moratorium, potentially explaining some of the remarkable increase in corn production seen in the Brazilian Legal Amazon since 2006. We find that leakage to corn can explain about 20% of the leakage to non-soy crops. Our results suggest that studies of the Soy Moratorium that have not allowed for substitution across crops may have overestimated its effect on deforestation.[3]

Finally, we find that *conservation zones* amplify the effect of agricultural commodity prices. On average, the prices in the years after zone expansions were 40% higher compared to the years before zone expansions. This led to about 6000 km^2 extra deforestation outside of the conservation zones compared to a situation without the zone expansions. One interpretation of our finding is that the deforestation could have continued into the new protected lands in the absence of the policy. The effects are similar if we include deforestation within the protected areas, which historically had low deforestation rates. Conservation zones take away land from the potential land supply and can thus increase the deforestation pressure on the remaining unprotected land. Our analysis, based on deforestation in non-conserved areas and explicit deforestation pressure, suggests that conservation

[1] The blacklisted municipalities were also called "priority" municipalities. Throughout the paper, we use the terms "priority" list policy and "black-listed" policy interchangeably.

[2] Arima et al. (2014) find that 10,653 km^2 of deforestation or 0.123 PgC of emissions were avoided over 2009–2011 in the targeted municipalities. Andrade and Chagas (2016) study spill overs of the blacklisting policy on non-targeted neighbouring municipalities and find a decrease of 15%–36% in deforestation in the non-listed neighbours. Koch et al. (2018) also find reduced deforestation in priority municipalities, but no effect on dairy production or crop production. , 2019b) find that the policy reduced deforestation by 40%, in period 2009–2010, and cut emissions by 39.5 million tons of carbon. PgC (petagrams of carbon) is the same as gigatonnes of carbon (GtC). The weight of CO2 is equal to 3.67 times the weight of Carbon, assuming that all the carbon is emitted. For more information on details of conversion of emissions measured in terms of carbon dioxide equivalent into carbon, see section 7.

[3] Gibbs et al. (2015) find that deforestation for soy dramatically decreased due to the Soy Moratorium, while Nepstad et al. (2014) find only a marginal effect of the Soy Moratorium. Svahn and Brunner (2018) find that the Soy Moratorium reduced deforestation in the Brazilian Amazon biome, but only after it was enforced with satellite monitoring since 2008.

zones have been less effective in reducing deforestation than existing studies have found.[4]

What is the cost of reducing carbon emissions through deforestation? We use data on the initial spatial variation in biomass in combination with deforestation over time to estimate carbon emissions. Comparing these emissions with the average crop production values that could be generated on deforested land, we arrive at carbon prices of about 6.5 USD/tCO_2. This is based on the unrealistic assumptions that all the carbon held in the cleared forest is emitted and that the mean crop yield per hectare captures the entire value of the additional agricultural activity. Both these assumptions are likely to imply that our calculated carbon prices are too low. Compared to other abatement technologies, our carbon prices do indeed suggest that reducing deforestation is a cheap abatement technology. For comparison, the High-Level Commission on Carbon Prices suggested that a global carbon price of USD 40–80/tCO_2 by 2020 and USD 50–100/tCO_2 by 2030 could allow the goals in the Paris climate agreement to be met (Stiglitz et al., 2017).

This paper makes two principal contributions to the growing literature on the drivers of deforestation and the effectiveness of policies against deforestation.[5] First, we focus on the effectiveness of policies explicitly accounting for the pressure to deforest, as expressed through international agricultural commodity prices.[6] Our analysis thus tests the robustness of environmental regulation when the pressure on natural resource use is high. A positive price shock resembles a positive shift in the demand curve for agricultural land. The priority list policy and the Soy Moratorium are expected to make the supply curve for agricultural land steeper, i.e. they increase the marginal cost of expanding agricultural land into forested lands (deforestation). A given price increase would then lead to a smaller expansion of agricultural land with the policy in place, compared to a situation without the policy in place. The conservation zones, on the other hand, are expected to shut down parts of the land market. The residual demand for non-protected land then increases, i.e. a given international price increase imposes a higher pressure on the remaining unprotected land. This results in a larger land expansion into unprotected lands with than without the policy in place. Deforestation pressure is discussed in the literature that tests policy effectiveness, e.g. Pfaff et al. (2014) and Assunção et al. (2015), but we explicitly bring in demand shocks. Based on our estimates, we graphically demonstrate that the effectiveness of a given policy measure in saving forest, measured in km^2, depends on the agricultural commodity prices.[7]

Second, this paper addresses the issue of policy ineffectiveness due to leakage (Aukland et al., 2003; Harstad and Mideksa, 2017). For the Soy Moratorium, we present evidence in support of substitution across crops, as the impact of non-soy prices increases under the moratorium. For conservation zones, we find increasing deforestation pressure due to prices when new areas are put under protection. In contrast, we find that the priority municipality policy is effective in reducing the impact of prices. Within municipalities, leakage reduces the effectiveness of the two policies that zoom in on specific sub-categories of deforestation, whereas the policy that targets deforestation irrespectively of its source is effective at the municipality level.[8] While the existing empirical literature has pointed to leakage across space, e.g. Pfaff and Robalino (2017) on conservation zones and Gibbs et al. (2015) on the Soy Moratorium, we are not aware that the leakage due to substitution across crops has been documented previously.

The remainder of this paper is organized as follows. Section 2 presents the institutional context. Section 3 discusses the data, the identification strategy and tests of parallel differential pre-trends. Section 4 presents econometric estimates of price effects and how they vary with respect to policy exposure. Section 5 investigates the impact of soy prices versus the prices of other crops under the Soy Moratorium. Section 6 presents robustness checks. Section 7 presents calculations of implicit carbon prices. Section 8 concludes.

[4] Assunção et al. (2015) find that about half of the avoided deforestation in the Brazilian Amazon over the period 2005–2009 was due to conservation policies. Soares-Filho et al., (2010) assign 37% of the reduction in deforestation in the Brazilian Amazon over the period 2004–2006 to expansion of protected areas. Also Nolte et al., 2013 find that protected areas have contributed to reducing deforestation rates. Anderson et al. (2016) find that conservation zones are mostly located in areas where agricultural production is likely to be unprofitable. They find that zones reduce deforestation if the incentives for municipalities to reduce deforestation are high.

[5] See Alix-Garcia et al. (2015), Alix-Garcia (2007), Assunção et al. (2015), Assunção et al. (2017), Assunção et al. (2019b), Barbier and Burgess (2001), Burgess et al. (2012), Burgess et al. (2017), Chomitz and Thomas (2003), Foster and Rosenzweig (2003), Gibbs et al. (2015) Pfaff (1999), Lopez and Galinato (2005), Rodrigue and Soumonni (2014), Rudel et al. (2005) and Hargrave and Kis-Katos (2013), as well as references therein.

[6] There is large empirical literature which has analyzed various impacts of booming commodity prices on commodity-exporting economies, i.e. macroeconomic performance and fluctuations (Deaton et al., 1995; Fernández et al., 2017; Drechsel and Tenreyro, 2018), structural adjustment via Dutch disease mechanisms (Harding and Venables, 2016; Cust et al., 2019) and conflict (Dube and Vargas, 2013; Bazzi and Blattman, 2014).

[7] Focusing on the interaction between prices and policies also helps with econometric identification, i.e. separating out the effect of the price-policy-interaction from the effect of other factors potentially affecting land demand or land supply. Our specifications allow us to control for a large set of observable and unobservable characteristics, including rich heterogeneity in the effect of prices, and we present evidence that the effect of prices is similar across control and treatment municipalities in absence of the policies. Existing studies have used several approaches to deal with endogenous placement of policies. Assunção et al. (2015), use a measure of the tightness of municipal land constraints, which is defined as the share of land that is not legally available to farmers relative to total municipal land, in order to identify the effect of policies across municipalities. Their approach is based on the argument that policies are effective in places where land constraints for agricultural production are tight. Assunção et al. (2017) argue that satellite-based enforcement contributed to reductions in deforestation rates and use cloud cover as an instrument. Assunção et al. (2019a), use a 2008-change in access to rural credit lines conditional on farmers' environmental compliance in order to show that this policy reduced deforestation rates in municipalities where cattle ranching is a dominant economic activity.

[8] We cannot, however, rule out that leakage happened somewhere else, a phenomenon documented previously in the literature (e.g., De Sá et al., 2013).

2. Background: key anti-deforestation policies in the Brazilian Legal Amazon

Our starting point is that agricultural profits are a major driver of deforestation.[9] Since 2004, Brazil has implemented a set of command-and-control and market-based policies to avoid the high deforestation rates it experienced in the 1990s and early 2000s, which to a large extent were related to expansion of commercial agriculture. Deforestation on private lands is governed by the Forest Code (FC), which establishes a percentage of rural properties that needs to be preserved in the form of native vegetation. In the Brazilian Legal Amazon, this fraction has been 80 percent since 2001 (Soares-Filho et al., 2014). In 2004, the National Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) was first launched. The plan set out new procedures for monitoring and environmental control. The first phase covered 2004–2008, the second phase 2009–2011 and the third phase 2012–2015. Arima et al. (2014); Assunção et al. (2015) and others have recognized a significant role of the different policies in reducing deforestation.

Blacklisting/priority municipalities policy (PM) was the main component of the second phase of the PPCDAm, launched in 2008. The policy defined a list of 36 municipalities to be prioritized in monitoring and law enforcement due to their high deforestation rates. The priority municipalities were subject to more intense environmental monitoring and enforcement as well as to a number of other administrative measures, such as more stringent conditions applied to the approval of subsidized credit. These measures have increased forest conversion costs and thus reduced incentives to deforest.[10] This group of municipalities accounted for 45% of the deforestation in the Brazilian Amazon in the year before the policy was implemented. More municipalities were added to the list later. During 2011–2013, eleven municipalities were allowed to leave the list due to a remarkable decline in deforestation. In the data section below we describe in more detail the variation in our sample.

The Soy Moratorium (SM) reflects intensive campaigning by non-governmental actors and private sector's willingness to adopt sustainable land-use practices. Soy has been Brazil's most profitable crop, with most of it going to exports; 33% in 1996 to 69% in 2004 and to 75% in 2013 (Karstensen et al., 2013; Lawson, 2014). A rapid expansion of soybean plantations on forested lands combined with the strong link to downstream markets in the EU and North America raised international awareness and increased the pressure on soybean producers to reduce deforestation. This led to the announcement of the Soy Moratorium in 2006. Buyers who joined the Soy Moratorium banned the purchase of soybeans planted on farmlands cleared after June 2006. The SM was extended to remain in place indefinitely in May 2016. The Soy Moratorium increases the costs of producing soy on newly deforested lands and thus increases the relative attractiveness of alternative uses of deforested lands, which can lead to substitution from soy to other crops. Supply-chain arrangements are incentive-based instruments and therefore the SM policy is an example of a market-based policy aimed at promoting environmental protection.

Conservation zones (CZ) expanded significantly in the Brazilian Legal Amazon in the early 2000s, especially during the first phase of PPCDAm. The areas that we name "conservation zones" in this paper include three types of protected areas: strictly protected areas (SP), sustainable use zones (SU), and indigenous lands (IL).[11] The policy of conservation zones takes away land from the potential land supply, and is thus expected to increase the value of, and the deforestation pressure on, the remaining unprotected areas.

CAR The government has made significant progress towards increasing enforcement of the Forest Code (FC) through mapping properties for environmental registration, first with a number of state-level systems in the Amazon, and more recently with a national "SiCAR" system.[12] The national system was finalized and became operational after 2013, when our sample period ends. However, CAR systems have been used in the zero-deforestation cattle agreements (Gibbs et al., 2016) and the Brazilian Central Bank's (BCB) rural credit policy, mentioned below (Assunção et al., 2019a). Two states, Mato Grosso and Pará, had the most developed state-level property registration systems preceding the SiCAR (INPE, 2015). To make sure that our results are not affected by factors correlated with the property registration, we take into account the area of properties registered in CAR in robustness checks.

Credit In February 2008, the Brazilian Central Bank published Resolution 3545, which conditioned the concession of rural credit for agricultural activities in the Amazon biome upon proof of borrowers' compliance with legal titling requirements and environmental regulation. Resolution 3545 applied to all rural establishments within the Amazon biome. It was obligatory for all banks and credit cooperatives to implement the terms of the resolution as of July 1st, 2008. As 30% of the resources required to fund a typical harvest year in Brazil come from the rural credit, Resolution 3545 represented a potentially limiting mechanism

[9] Commodity prices may carry not only information about current land use opportunities (forest vs pasture) and manifest through changes in *current* agricultural profits, but also through *expected revenues* from future land use. The latter effect manifests itself through a speculative component of the value of the land. In this paper, we do not differentiate between the effects on deforestation caused by current versus future land opportunities. Furthermore, these policies could also affect deforestation through mechanisms other than agricultural commodity prices, such as enforcement of the forest code or the value of standing forest (which in turn depends on timber prices, policy, and enforcement). Our analysis does not capture such other possible mechanisms.

[10] In addition to a more stringent system of monitoring and law enforcement, they also became subject to a series of other measures, not officially established through legislation, such as compromised political reputation of mayors (Abman, 2014), politicians pressuring farmers to comply with environmental legislation. Priority status is determined based on: (a) total deforested area; (b) total deforested area over the past three years; and (c) increase in the deforestation rate in at least three of the past five years. The middle maps of Fig. 1 show that these municipalities are mainly located in the southern part of the Amazon region, along the arc of deforestation.

[11] In SP: harvesting of trees or settlements are prohibited completely. In SU zones, extraction of forest resources as well as logging are permitted subject to a sustainable management standard Verissimo et al. (2011). IL are federal territories which are in the permanent possession of indigenous populations, who have exclusive rights to use the natural resources.

[12] Sistema Nacional de Cadastro Ambiental Rural, SiCAR 2016.

for agricultural production in Brazil. Estimates by Assunção et al. (2019a) indicate that the total observed deforested area from 2009 through 2011 was about 60% smaller than it would have been in the absence of credit restrictions. We thus control for credit in robustness checks.

Fines The real-time System for Detection of Deforestation (DETER), developed by the National Institute for Space Research (INPE), has been Central to the PPCDAm's law enforcement. DETER is a satellite-based system that captures and processes geo-referenced imagery on forest cover in 15-day intervals. This allows authorities to identify deforestation hot spots and enforce the law with a much shorter lag. In addition to the adoption of DETER, the PPCDAm promoted institutional changes that enhanced the monitoring and law enforcement capacity in the Amazon, e.g., through more and better qualified law enforcement personnel. Assunção et al. (2017) use the total number of fines issued by Ibama, the Brazilian regulator, in each municipality as a proxy for the intensity of law enforcement activity. They estimate that deforestation observed from 2007 through 2011 was 75% lower than it would have been in the absence of the fines. We control for fines in robustness checks.

3. Empirical approach

3.1. Data

Our initial data set is a balanced panel of 771 municipalities in the Legal Brazilian Amazon from 2002 until 2013. We drop municipalities that on average have zero deforestation, zero remaining forest or a price index equal to zero. In addition, we drop municipalities with average forest cover below the 1st percentile and above 99th percentile. In our baseline sample, we focus on municipalities located within the forest frontier, the "arc of deforestation," which are to a large extent located along the transition from the Amazon to the Cerrado (tropical savanna) biomes (Levy et al., 2018). Historically, the deforestation in Brazil started in the south east and has swung in the north-western direction over time. The smooth lines in the two upper maps of Fig. 1 show the "arc of deforestation", which includes three areas based on different historical periods of deforestation. We include all municipalities that have some area that falls within either of the three areas. We end up with a balanced panel of 470 municipalities covering 11 years (2003–2013, with lagged variables for 2002–2012). For a complete overview of data sources and the relevant variables used in this paper, see Tables A.1–A.2. Below, we provide more information on the most central variables.

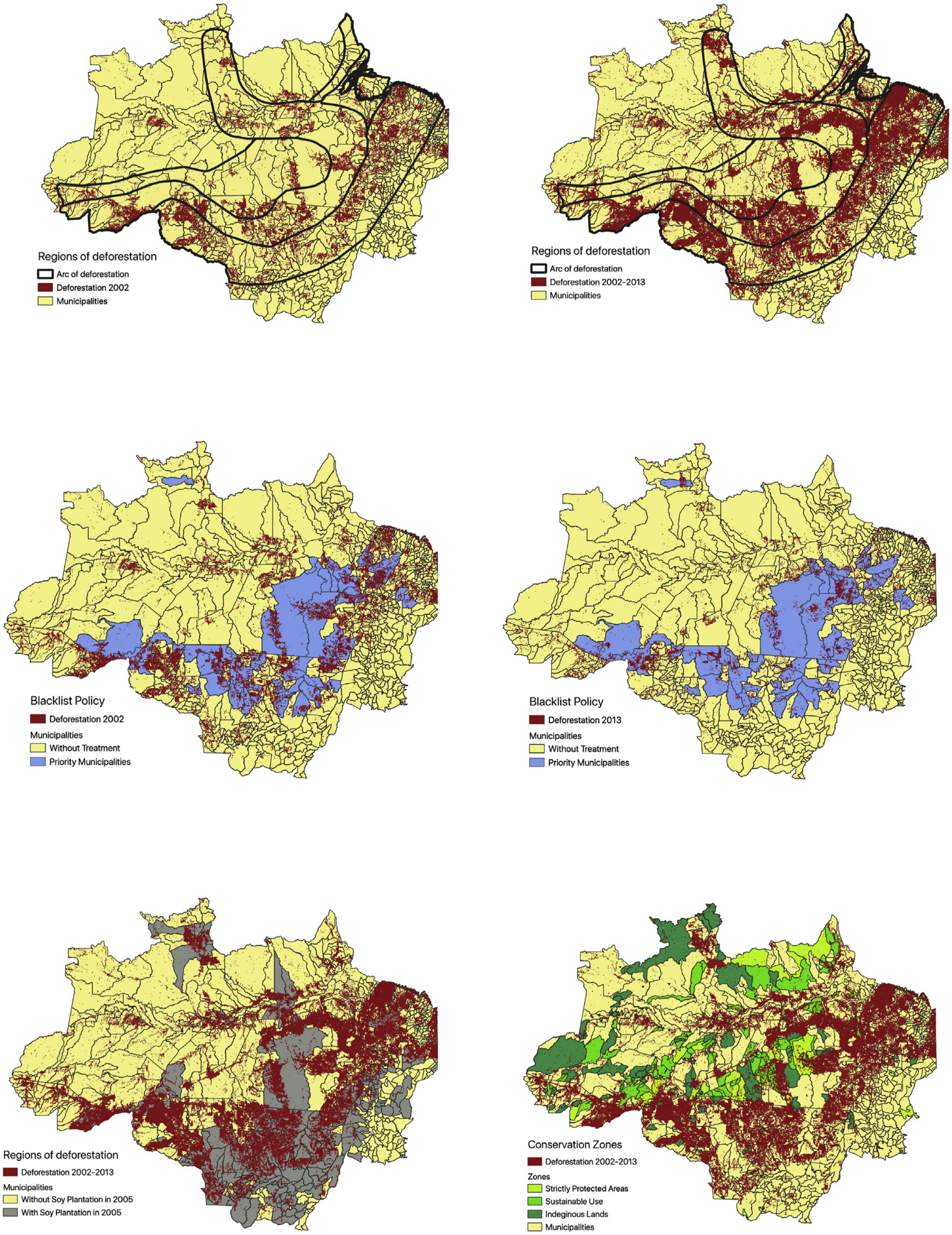
Forest data For annual data on deforestation and forest cover we use data based on NASA satellite images and processed by the Brazilian Space Research Agency, *Instituto Nacional de Pesquisas Espaciais (INPE)*. This processing includes filtering out forest plantations and the data provide the loss of primary forest. We have aggregated the high-resolution forest data (at 250 m × 250 m) to 1 km^2 grid cells covering the entire Brazilian Legal Amazon (BLA). For each municipality, we consider the sum of cells outside of conservation zones, the sum of cells inside of conservation zones, and the sum of cells both inside and outside of conservation zones. In our main analyses, we focus on areas outside of conservation zones. We measure deforestation and forest cover in km^2. The red dots in the upper right map of Fig. 1 indicate the sum of deforestation over 2002–2013 at the 1 km^2 resolution. The left panel of Fig. 2 presents the sum of deforestation over time in our sample of 470 municipalities.

Carbon data We use biomass data from Baccini et al. (2017) and obtain the carbon stock in the year 2000 at the 1 km^2 grid-cell level (C_{2000}). Carbon is set to 0.5 of the biomass (like for example in (Saatchi et al., 2007)). For each grid cell, we calculate the carbon stock in year t as the remaining forest, F_t, times the carbon density of the forest in that grid cell in year 2000: $C_t = F_t^* C_{2000}/F_{2000}$. Analogously, we calculate the carbon flow as deforestation, DF, times the carbon density in year 2000: $DC_t = DF_t{}^* C_{2000}/F_{2000}$. We recalculate the carbon to CO_2, i.e. multiply the carbon figures by 44/12. We thus assume, for simplicity, that all the carbon in the cleared forest is turned into omitted CO_2, which is unrealistically high as, for example, some forest may be used as building materials. The right panel of Fig. 2 presents the loss of CO_2 over time in our sample, again for the outside of conservation zones and for the total. To further simplify the cost-benefit analysis, we convert carbon to dollars by valuing the CO_2 to 50 USD per tonne (2020-prices). This a simple and seemingly not unreasonable estimate for the social cost of carbon in 2020 (see for example Howard and Sylvan (2015)).

When we calculate the implicit price of carbon in section 7, we ignore sequestration, i.e. the carbon the forest could have absorbed continuously if it were kept standing. We do not have precise estimates for it in our data. Hubau et al. (2020) estimate that "intact old-growth tropical forests" in Amazonia sinks about 0.4 tonne Carbon per hectare per year, which corresponds to about 1.5 tonnes of CO_2 per hectare forest, or USD 75 at 50 USD/tCO_2. As our estimates for deforestation and carbon imply CO_2 values of about USD 20,000 per hectare, the sequestration would thus add only about 0.4% of the carbon stock per hectare per year.[13] Standing forests do also provide benefits beyond carbon capture and storage, e.g., biodiversity, that we also do not pick up with our stylized carbon valuation. Finally, if the forest were allowed to grow back instead of the area being turned into non-forest permanently, regrowth of new forest could mean higher absorption of carbon than the previous forest. In our context, this is likely to be rare as we focus on the effect of agricultural commodity prices on deforestation.

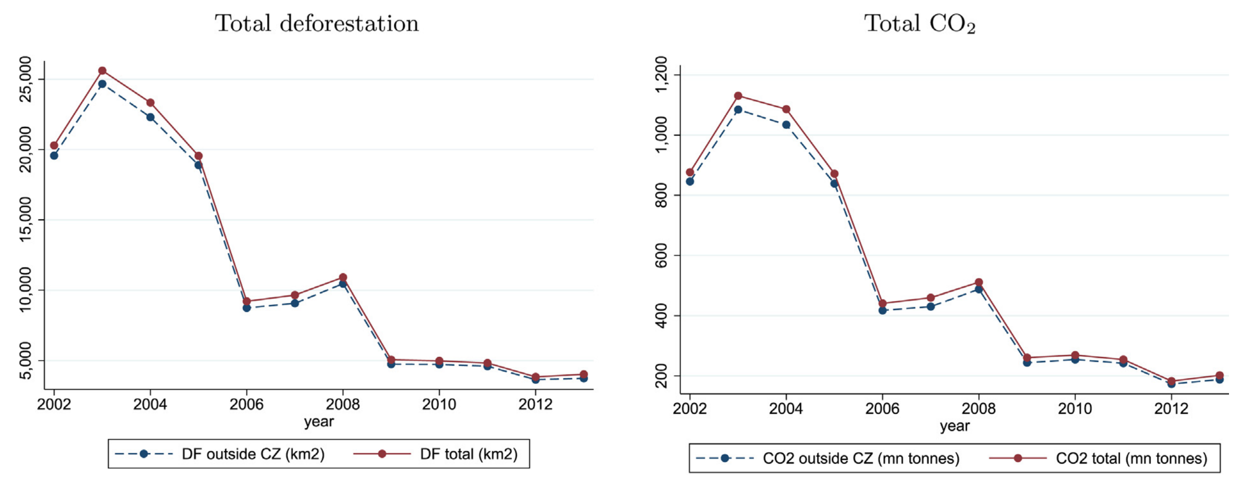
Data on production values in agriculture IBGE provides data on annual production value for each crop at the municipality-level. We deflate these values with the deflator used by the World Bank in their Pink Sheet, i.e. the same deflator that is used

[13] Clearing a hectare of forest thus corresponds to the removal of a present value of about 750 USD per hectare in terms of lost carbon sequestration at a discount rate of 10%: 75/0.10. We would assume that this is the difference between the sequestration of forest and the sequestration of the cleared land.



Note: Maps show: in the top row, the forest frontier together with deforestation in 2002 and accumulated deforestation over 2002-2013; in the middle row, the municipalities ever on the priority list in our sample together with deforestation in 2002 and 2013; in the bottom row, the municipalities exposed to the Soy Moratorium as they planted soy in 2005 and the three types of protected lands included in this paper's "conservation zones".

Fig. 1. Maps of policies and deforestation. The shapefile for Brazil is from INPE/IBGE and the shapefile for the "arc of deforestation" is from IMAZON.



Note: Total deforestation and lost CO_2 in our baseline sample (forest frontier), outside of conservation zones only as well as inside and outside of conservation zones.

Fig. 2. Deforestation and CO_2.

to deflate our agricultural commodity prices. We recalculate such that the figures are in real 2020-USD.[14] Clearly, there may be other economic benefits related to expanding the agricultural sector that are not captured by crop production values. We also ignore the sales of timber.

Priority municipalities The Brazilian Department of the Environment, *Ministério do Meio Ambiente, MMA*, publishes the list of municipalities with a “priority” status, including the date they entered the list. The left map in the middle row of Fig. 1 shows deforestation and the listed municipalities in 2002, long before the policy was implemented, while the map next to it illustrates the deforestation in 2013. In our sample, a total of 50 municipalities were blacklisted. 33 got on the list in 2008, 8 in 2009, 7 in 2011 and 2 in 2012. None of the municipalities in our sample got off the list during the period we study. The weighted mean length on the list is 5.5 years in our sample. For the empirical analysis, we generate an “Active” dummy (denoted A) taking one for the years a municipality was on the list and an “Ever” dummy (denoted E) indicating whether a municipality was blacklisted at any point in time during the sample period.

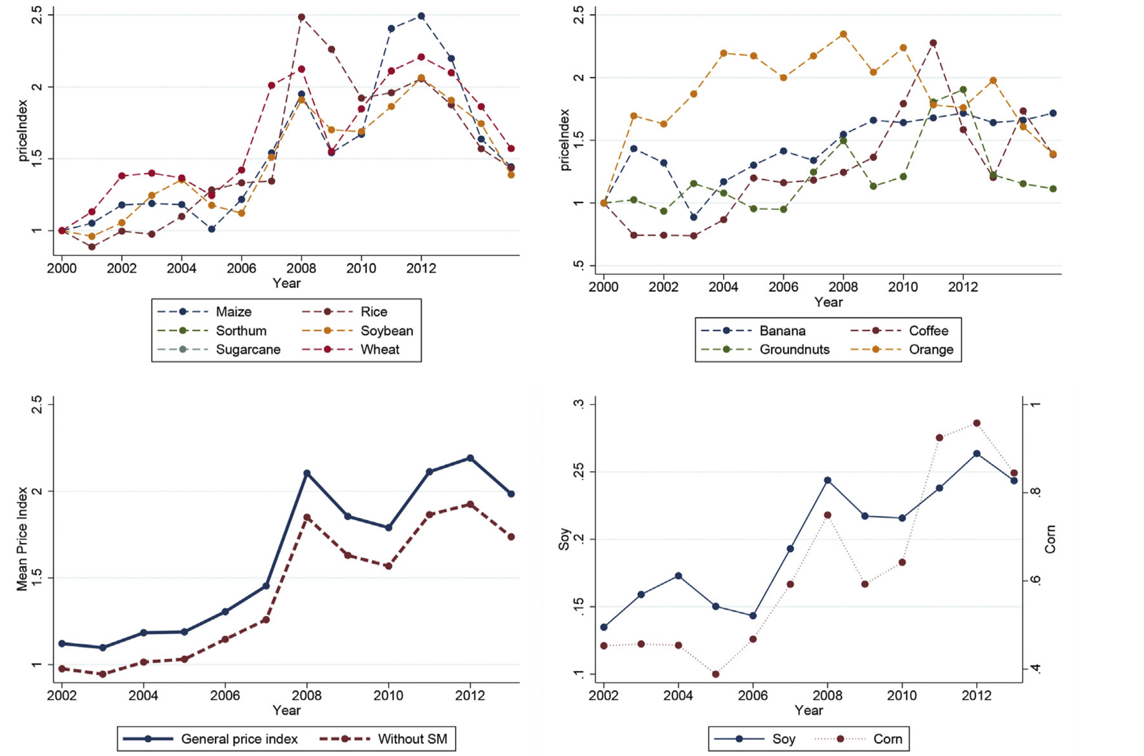
Soy Moratorium We classify the treatment group as those municipalities that produced soybeans in 2005, the year before the Soy Moratorium started. Data on the planted area and production volume of soy are published in the municipal agricultural report *Produção Agrícola Municipal* from IBGE (2017). The lower left part of Fig. 1 maps the 190 municipalities in the entire Brazilian Legal Amazon that planted soy in 2005 according to the IBGE data. For reference, 201 municipalities planted soy in 2013. In our sample, the IBGE data suggest that 147 municipalities planted soy in 2005. We now define the “Ever” variable E as the log of the area in km^2 allocated to soy in 2005. The “Active” dummy A is now simply one for all years after 2005.

Conservation zones Data on implementation dates and locations of protected areas were obtained from the Brazilian Ministry of Environment MMA (2017). There are 258 protected areas implemented between 2003 and 2013: 48 strictly protected zones, 92 sustainable use zones and 118 indigenous lands. The lower right part of Fig. 1 illustrates how they are distributed over the Brazilian Legal Amazon. In our sample, there were 5 municipalities with at least one of the three types of protected areas in 2003, covering in total between 2.6% and 10.6% of the municipality areas. In 2013, 136 municipalities had such conservation zones, covering between 0.4% and 73.4% of the municipality areas. 0.25% of the 3.2 million km^2 covered by our sample of 470 municipalities were covered by one of the three types of protected areas that we consider as conservation zones in 2003. In 2013, this number had increased to 17.2%. For the empirical estimation, the variable A is the log of the area in km^2 located in a conservation zone in a municipality. The dummy variable E takes one if the municipality expanded the area covered by conservation zones in the sample period.

International prices We obtain international crop prices from the World Bank. Data on the land allocated to each crop in a municipality are provided by an annual survey of agricultural production across all Brazilian municipalities from the IBGE. In our price index, we include ten internationally traded crops: banana, coffee, groundnut, maize, orange, rice, sorghum, soybean, sugar cane, and wheat. Together they account for over 80% of the agricultural area in the Amazon region.[15] Soy occupies the most crop-planted area in the Amazon. The area planted with soy increased from 41,965 km^2 in 2002 to 66,976 km^2 in 2006. It

[14] For the commodity prices in nominal and real values, see Pink Sheet, World Bank. The base year in the deflator is 2010. We use the exchange rate 1BR = USD 0.60, as off 30 dec. 2010 (The Federal Reserve).We arrive at 2020-figures by using the accumulated inflation in the US since 2010, i.e. 18.8% (US CPI)).

[15] The most frequently (but not most extensively) planted crop in the Amazon, which is not part of our price index, is cassava. Cassava plantation accounted for less than 4% of the agricultural area in 2013. We exclude cassava since it is not an export crop, but mainly planted for own consumption or the domestic market.



Note: Upper charts present indexes of the real international agricultural prices, which we combine with municipality weights based on cultivated area in 2002 to construct municipality specific price indexes. Lower left chart shows the average of the general price index across municipalities, with and without soy. Lower right chart presents the mean of the municipality specific price indexes for soy and corn separately.

Fig. 3. Price indexes.

further increased to 93,504 km^2 in 2013, which corresponds to about 53% of all crop fields in the region. Corn, the second largest crop, increased its share from around 16% in 2002 to over 25% in 2013. Sugar cane is another important monocultural crop that is mainly produced in the south of Brazil, but is also increasingly being planted on recently deforested land in the legal Amazon (Martinelli and Filoso, 2008).

We construct our municipality-specific price index as follows:

$$P_{a,it} = \sum_j w_{ij,2002} P_{jt}, \quad w_{ij,2002} = \frac{area_{ij,2002}}{\sum_j area_{ij,2002}} \tag{1}$$

where P_{jt} is the international price measured in current \$US of crop j at time t, normalized to 1 in year 2000. The weights $w_{ij,2002}$ are calculated based on the size of the planted area of crop j in municipality i in 2002, the initial year in our sample. We use these predetermined weights to avoid that the price index itself is affected by the farmers' behavior during the period we study. The weights sum to one. When we use the soy, non-soy and corn prices separately in the context of the Soy Moratorium, we apply Equation (1) with weights based on 2005, the year before the introduction of the Soy Moratorium. As the weights are then for a subset of crops, they do not sum to one. We provide robustness checks with alternative weights, as described in section 6. Fig. 3 presents the price indexes we use.

Controls. We account for: (i) rural credit policy, by including the normalized total value of credit concessions in a given municipality in a given year; (ii) for overall level of stringency of monitoring and law enforcement, by using the log of the annual number of environmental fines applied at the municipality level in the previous year.[16] In addition, we perform a large number of other robustness checks in section 6, where we also run robustness with respect to the CAR policy.

[16] We are very grateful to Juliano Assunção, Clarissa Gandour, Romero Rocha and Rudi Rocha for sharing with us their data on rural credit and fines.

3.2. Identification strategy

In our empirical strategy we proceed in three steps. First, we estimate the relationship between commodity prices and deforestation with the following equation:

$$DF_{it} = \beta_1 P_{a,it-1} + I_t + I_i + \epsilon_{it} \tag{2}$$

where DF_{it} denotes the log of the sum of deforestation in municipality i in year t (August t-1 to August t). $P_{a,it-1}$ is the log of the municipality-specific price index of global commodity prices, with area allocated to the respective crops in 2002 as the weights (see section 2). I_i and I_t refer to municipality and year fixed effects. The coefficient of interest, β_1, is identified to the extent the error-term ϵ_{it} is uncorrelated with $P_{a,it-1}$, which is plausible given the pre-determined weights and international prices.[17] Standard errors are clustered at the municipality level.

Second, we estimate how policies aimed at reducing deforestation affect the deforestation's response to international commodity prices. We expand equation (2) with the policy exposure at the municipality level. This amounts to estimating a triple differences model (DDD). Formally, we estimate DDD-models of the following form:

$$\begin{aligned} DF_{it} = {} & \beta_1 P_{a,it-1} + \beta_2 P_{a,it-1} \times E_i \times A_{it} + \beta_3 P_{a,it-1} \times E_i^{dum} + P_{a,it-1} \times I_t \beta_4 + \beta_5 P_{a,it-1} \times F_{it-1} \\ & + \gamma_1 F_{it-1} + \lambda_1 E_i \times A_{it} + E_i^{dum} \times I_t \lambda_2 + I_t + I_i + \epsilon_{it} \end{aligned} \tag{3}$$

The main parameter of interest is β_2 (the triple difference estimate), indicating how the price-effect depends on the presence of the policy. $E_i \times A_{it}$ is the policy treatment variable. For the blacklisting policy, it takes one if a municipality is on the blacklist in a given year and zero otherwise. For the soy moratorium, the policy treatment variable takes zero for the years before 2006 and then switches to the log area devoted to soy production in the year before the moratorium was introduced. For the conservation zones, the policy treatment variable is the area allocated to conservation zones in any given year. The variable E_i^{dum} indicates whether the municipality is ever directly exposed to the policy. For simplicity, we define it as a dummy for all three policies. It takes one if the municipality is ever on the blacklist, the area devoted to soybeans in the year before the Soy Moratorium is larger than zero,[18] or there is an expansion of protected areas in our sample period.

We include the interaction between the price and the ever dummy, E_i, allowing for a different price effect across the control and treated municipalities in all years. A full DDD-model requires the price to be interacted with the post dummy. We use instead the more flexible specification of interaction between the price and the year dummies, to allow for a differential price effect across all municipalities over time.[19] We include interactions between the ever dummy and the year dummies, to flexibly allow for different trends between the treatment and control groups. Note that the policy treatment variable $E_i \times A_{it}$ is not collinear with these time-dummy interactions for the respective reasons: municipalities were put on the blacklist at different times; the area devoted to soy varies across municipalities; and the size and the timing of the conservation zones varies across municipalities. Finally, we include log of lagged forest cover, F_{it-1}, and its interaction with the price index.

To keep the model tractable, we estimate equation separately for each policy. We present estimates where we include all three policies simultaneously in section 6.[20] We there also discuss threats to identification and show robustness to a host of controls and other policies.

3.3. Testing for parallel pre-trends

Our key identifying assumption is that, in absence of the policies, the treated and non-treated municipalities would have had the same difference-in-differences in deforestation with respect to high and low price exposure. This identifying assumption is untestable, but we follow Muralidharan and Prakash (2017) and use the pre-policy data in Table 1. As indicated by the first row in columns 1–3, we can reject parallel trends for the policies in a DD-specification, i.e. when we compare only across the control and treatment group. Bringing in the agriculture commodity prices in columns 4–6, however, we cannot reject common differential trends as seen by the triple interaction term in row 3.

In Tables A.5–A.7, we present pre-trend tests for 12 covariates. The coefficient on the triple interaction term is statistically insignificant in all cases, with the following few exceptions: the size of the area used for agriculture for the priority list policy; agriculture productivity and remaining forest for the conservation zones; and one or more credit measure for all three polices. However, we show in section 6 that our results are robust when we include any of these characteristics as controls.

The pretrend-tests increase our confidence that our key identifying assumption is satisfied.

[17] Global commodity prices combined with various local weights have been used in similar specifications in the literature on conflict (Dube and Vargas, 2013; Bazzi and Blattman, 2014) and in the literature on the Dutch disease (Harding and Venables, 2016; Cust et al., 2019).

[18] In Table A.8, we use the log area soy planted in 2005 instead of treatment group dummy for the SM.

[19] Note that the direct price effect, β_1, is absorbed by the interactions with the year dummies. Note that β_4 and λ_2 are vectors of coefficients.

[20] See Appendix Table A.9.

Table 1
Testing for parallel pre-trends.

	(1) PM DD	(2) SM DD	(3) CZ DD	(4) PM DDD	(5) SM DDD	(6) CZ DDD
TreatGr = 1 × Trend	−0.065*	0.094*	−0.124**	−0.129	−0.053	−0.116
	(0.038)	(0.054)	(0.056)	(0.091)	(0.108)	(0.111)
TreatGr = 1 × L.Price				2.670	−4.198	−1.030
				(1.859)	(2.556)	(2.100)
TreatGr = 1 × Trend × L.Price				−0.147	1.039	0.387
				(0.398)	(0.680)	(0.620)
Trend × L.Price				−0.194	−2.737***	−2.597***
				(0.145)	(0.376)	(0.489)
L.Price				1.870***	8.700***	8.030***
				(0.586)	(1.289)	(1.633)
Observations	2350	1410	1410	2350	1410	1410
Municipalities	470	470	470	470	470	470
R-sq	0.27	0.03	0.03	0.28	0.10	0.10

Note: The dependent variable is log of deforestation in a municipality in the years before the policy was implemented. DD indicates difference-in-difference versus DDD indicates triple differences, where the price variable represent the third difference. The price index is calculated by Equation (1) and included in the log-form. All area sizes used for the price-weights are measured at the municipality level for the year 2002, the initial year in our sample. *Trend* is a trend variable, defined as Year-2001. *TreatGr* indicates if a municipality is in the control or treatment group. In columns 1 and 4, the assessed policy is the blacklisting policy (2002–2007), in columns 2 and 5 it is the Soy Moratorium (2002–2005) and in columns 3 and 6 it is the conservation zones (2002–2005). We take 2006 as the treatment year for conservation zones since it was the year with the highest expansion in protected areas. Includes municipality and year fixed effects. Standard errors are in parenthesis and clustered at the municipality level.

Table 2
Baseline results prices and policies.

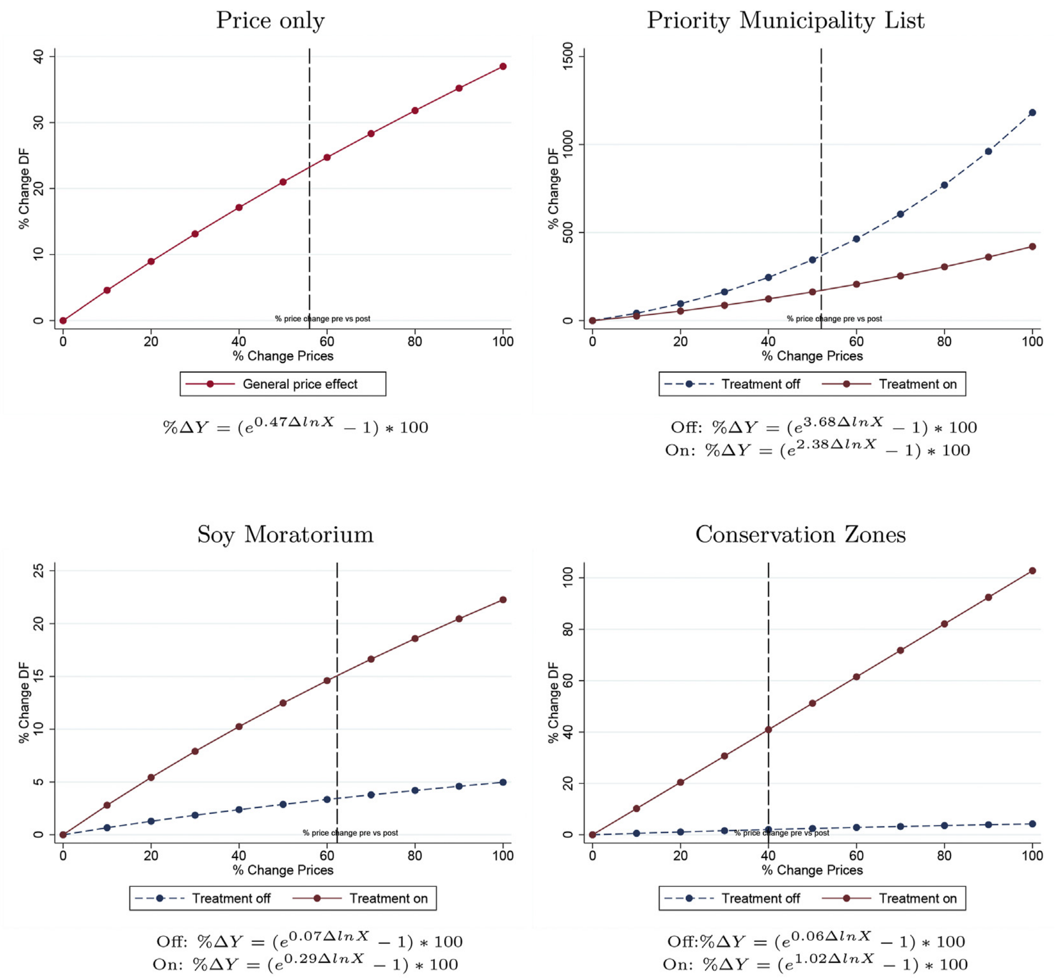
	Prices only		
	(1) Price	(2) Price	(3) Price
L.Price	0.491***	0.654	4.222***
	(0.190)	(0.469)	(0.553)
L.Forest cover			2.382***
			(0.147)
L.Forest cover × L.Price			−0.305***
			(0.020)
Observations	5170	5170	5170
Municipalities	470	470	470
R-sq	0.41	0.41	0.48
I x P			Yes
Total price effect			
dydx(P)	0.49	0.49	0.47
p-value	0.01	0.01	0.01

Note: The dependent variable is log deforestation in areas outside of conservation zones. The price index is calculated by Equation (1) and included in the log-form. All area sizes used for the price-weights are measured at the municipality level for the year 2002, the initial year in our sample. Models are versions of Equation (2), where column 2 includes trend and trend interacted with the price and column 3 includes interactions between year dummies and the price. All columns include municipal and year fixed effects and the standard errors shown in parentheses are clustered on the municipality level. The bottom rows give the price effects. The p-values are from an hypothesis test where H0 is that the effect listed above is zero. The marginal effects and the p-values are calculated with the margins package in stata.

4. Agricultural commodity prices and policy impact

Table 2 presents versions of equation (2), which confirm that higher agriculture commodity prices exert higher pressure on the forest. Column 1 simply includes municipality and year fixed effects in addition to the municipality specific price index. Column 2 adds time trend interaction with the price and column 3 adds time fixed effects interaction, lagged forest cover and interaction between the price and the lagged forest cover.[21] The results show that a one percent increase in the price index

[21] The price effect is stronger in municipalities with lower levels of remaining forests, as shown in column 3. Such heterogeneity is not surprising given that our sample covers 470 municipalities and about 3 million square km.



Note: The figure illustrates the relative annual deforestation changes (Y) at different relative price changes (X). The estimates are based on columns 3 in Table 2 and 4-6 in Table 3 and the graphs are based on the formulas shown below each chart. For the three policy-charts, the difference between the two lines is the treatment effect on the treated. Vertical lines indicate the actual average price changes observed for the treated municipalities between the pre-treatment period and the treatment period.

Fig. 4. Deforestation under different prices and treatments.

increases deforestation by 0.47 percent. As the level of the price index over 2004–2013 was on average 56% higher than in 2003, this estimate implies that the annual deforestation was on average 23% higher than it would have been with the 2003-prices. The higher prices led to about 3.7 km^2 higher annual deforestation per municipality on average, corresponding to a total of about 17,200 km^2 across the 470 municipalities over the 10 years (see Table A.4).[22] The upper left panel of Fig. 4 presents the estimated relationships between percentage increases in the price index and percentage increases in deforestation, with the observed price increase of 56% indicated with the vertical dashed line.

Our main question is whether the priority municipality list (PM), the Soy Moratorium (SM), and conservation zones (CZ) reduce the pressure of higher commodity prices on deforestation. Table 3 presents our baseline estimates: Columns 4–6, based on Equation (3). Columns 1–3 correspond to the DDD-specification in the pre-trend test Table 1 and are included for completeness. The main parameter of interest is the triple-difference estimate (captured by variable *TreatGr* × *Active* × *L.Price*). We present the total price effect with and without the policy in the two bottom rows of the table, together with the difference between them and the p-value for the hypothesis test that this difference is equal to zero. Fig. 4 shows the total price effects with and without the policies and illustrate the main point of this paper: the effect of the regulatory policies depends critically

[22] To compute the overall level of deforestation, we multiply the average reduction in deforestation due to the higher prices (ΔY_{cf}) with the total number of treated municipalities over the period of the policy (N).

Table 3
Baseline results prices and policies.

	Policies (trend)			Policies (Eqn 3)		
	(1) PM	(2) SM	(3) CZ	(4) PM	(5) SM	(6) CZ
TreatGr x Active × L.Price	−1.473**	−0.154***	0.088**	−1.301**	0.027	0.168***
	(0.574)	(0.037)	(0.038)	(0.595)	(0.036)	(0.031)
L.Forest cover				2.335***	2.578***	2.249***
				(0.145)	(0.155)	(0.149)
L.Forest cover × L.Price				−0.286***	−0.285***	−0.376***
				(0.022)	(0.020)	(0.022)
Observations	5170	5170	5170	5170	5170	5170
Municipalities	470	470	470	470	470	470
R-sq	0.42	0.44	0.41	0.49	0.52	0.50
I x P				Yes	Yes	Yes
Total price effects, policy off/on						
dydx(P) policy off	0.74	0.80	0.16	3.68	0.07	0.06
p-value	0.12	0.02	0.56	0.00	0.85	0.84
dydx(P) policy on	−0.73	−0.06	0.67	2.38	0.29	1.02
p-value	0.15	0.81	0.00	0.01	0.40	0.00
Difference in total price effect						
Difference	−1.47	−0.86	0.50	−1.30	0.22	0.96
p-value	0.01	0.00	0.02	0.03	0.45	0.00

Note: The dependent variable is log deforestation in areas outside of conservation zones. The price index is calculated by Equation (1) and included in the log-form. All area sizes used for the price-weights are measured at the municipality level for the year 2002, the initial year in our sample. Columns include policies as indicated in the column headings. *Ever* and *Active* is defined according to the policy type as described in section 3. Columns 1–3 include time trends interacted with the price index as well as with the ever-treated dummy. Columns 4–6 are based on Eqn 3 and include interactions between the price and year dummies and interactions between the ever-treated dummy and year dummies. All columns include municipal and year fixed effects and the standard errors shown in parentheses are clustered on the municipality level. The bottom rows give the price effects, with and without the policy for the treated when relevant. The p-values are from an hypothesis test where H0 is that the effect listed above is zero. The marginal effects and the p-values are calculated with the margins package in stata.

on the underlying deforestation pressure.

Comparing the effect of agriculture commodity prices on deforestation with and without the policies, as listed in the bottom rows in Table 3, we find that the priority list reduces the effect by about 1.3 percentage points (3.68–2.38). The effect is statistically significant. The price increase of 52% from the pre-policy period 2003–2007 to the post policy period 2008–2013 would have led to a 370% increase in deforestation in the treatment group in absence of the policy. With the policy in place, the price increase leads instead to a 172% increase in deforestation. Using the actual observed deforestation for the municipalities in the treatment group over the period 2008–2013, the priority list saved 35 km^2 of forest in every treated municipality on average per year, which sums up to about 9,100 km^2 overall (see Table A.4 for the details of these calculations). The upper right chart of Fig. 4 illustrates how the policy contributes to avoiding large increases in deforestation when the price growth is high.

The Soy Moratorium does not have a statistically significant effect on how commodity prices affect deforestation, and the sign of the estimated coefficient actually suggests that the Soy Moratorium raised the deforestation pressure. This can also be seen in the lower left chart of Fig. 4. We further explore the effects of the Soy Moratorium for the soy price, non-soy prices and the corn price in section 5.

Conservation zones amplify the price effect, which can be seen in the lower right chart of Fig. 4. For illustration, we use the average price in the pre-policy years and the average price in the post policy years, i.e. 1.31 and 1.83, where the pre and post policy years vary at the municipality level. Due to this 40% increase in the price index, expansion of zones increased annual deforestation outside of zones by 6.1 km^2 per municipality or a total of about 6,100 km^2 (see Table A.4). These results are consistent with zones taking away land from the land supply and hence they increase the pressure on the remaining land. It is also possible that establishing conservation zones increases rivalry for remaining land and thus increases deforestation as a means of taking land into possession.[23]

Fig. 4 makes clear that we in this paper study the effect of the policies through agricultural commodity prices, i.e. through the change in the opportunity cost of farming forested land. The policies may also work via other channels. For instance, the policies may simply increase the cost of deforestation through higher risk of, or higher penalties for, getting caught for illegal deforestation, which are separate from the opportunity cost of agriculture. Similarly, the value of the standing forest may also

[23] As mentioned in section 2, property rights in the Amazon are not well defined or defended. Thus, deforestation is still seen as a practice to obtain land titles which otherwise could be lost through invasion or expropriation (Fearnside, 2001). For completeness, we present estimates where the dependent variable is the deforestation within conservation zones only (lower column 4 in Tables A.10–A.15) and deforestation in the entire municipality (lower column 5 in Tables A.10–A.15). For deforestation inside zones, we do not find any significant differences in the price effect. The results based on deforestation in the entire municipality are very similar to the baseline results.

Table 4
Soy moratorium with different price indexes.

	SM: Different Prices (Eqn 3)		
	(1) Psoy	(2) Pnon-soy	(3) Pcorn
TreatGr x Active × L.Price	−0.055**	0.104***	0.017*
	(0.023)	(0.024)	(0.009)
L.Forest cover	2.629***	2.600***	2.150***
	(0.630)	(0.153)	(0.154)
L.Forest cover × L.Price	−0.363***	−0.292***	−0.224***
	(0.037)	(0.019)	(0.016)
Observations	1584	5170	5137
Municipalities	144	470	467
R-sq	0.64	0.52	0.50
I x P	Yes	Yes	Yes
Total price effects, policy off/on			
dydx(P) policy off	0.84	−1.13	3.97
p-value	0.19	0.00	0.05
dydx(P) policy on	0.39	−0.28	4.11
p-value	0.54	0.31	0.05
Difference in total price effect			
Difference	−0.45	0.85	0.14
p-value	0.02	0.00	0.05

Note: The dependent variable is log deforestation in areas outside of conservation zones. The table repeats column 5 of Table 3, but with alternative prices: Column 1 is based on the area of soy planted times the soy price. Column 2 is based on the agricultural price index excluding soy, using the area sizes allocated to each crop as weights (following Equation (1)). Column 3 is based on the area of corn planted times the corn price. All area sizes used for the price-weights are measured at the municipality level for the year 2005, the year before the soy moratorium was introduced. All the price-variables are included in the log-form. All columns include municipal and year fixed effects. Standard errors are clustered at the municipality level. The bottom rows give the price effects, with and without the policy for the treated when relevant. The p-values are from an hypothesis test where H0 is that the effect listed above is zero. The marginal effects and the p-values are calculated with the margins package in stata.

change due to the policies, as expected timber prices or the expected surrounding landscapes may change. In this paper, we do not seek to identify these other potential channels.

5. Soy moratorium and different crops

An important finding of this paper is that the Soy Moratorium does not reduce the impact of commodity prices on deforestation. This seems to stand in contrast to the influential study by Gibbs et al. (2015), which found that the Soy Moratorium is effective in reducing deforestation. The authors studied the extent to which soy has been cultivated on newly deforested land after the Soy Moratorium was introduced. In this section we show that the Soy Moratorium reduced the responsiveness of deforestation to the soy price, but that this was counteracted by an increased responsiveness to the price of other crops.

In Table 4, we present estimates of our triple difference model, again based on (3), for the Soy Moratorium under different commodity price indexes. In column 1 we use a soy price index, in column 2 a price index excluding the soy price and in column 3 a corn price index. The negative and statistically significant coefficient of the triple interaction term in column 1 suggests that the Soy Moratorium significantly reduced deforestation related to the soy price. The magnitude means that the policy reduced annual deforestation by 2.3 km^2 per treated municipality and by about 2,650 km^2 in total (see Table A.4 for the details).

Column 2, however, indicates that the impact of non-soy prices on deforestation increased significantly in the presence of the Soy Moratorium. The deforested area increased by 5.1 km^2 annually per municipality and about 5,850 km^2 in total due to higher prices of other crops. As a result, the net increase in deforestation due to the policy is estimated at about 3,200 km^2 (Table A.4).

Corn is a non-soy crop that has experienced remarkable expansion in recent years. While corn was a minor crop in the Brazilian Legal Amazon in 2006, corn production has since then quadrupled and become the second most important crop in the Legal Amazon in terms of export share, after soy (IBGE, 2017). In recent years, soy and corn combined accounted for over 95% of the vegetable exports of the region (SECEX, 2017). Corn has been found to grow under the same climatic and geological conditions as soy, and substitution between soy and corn in the soy producing areas is thus feasible (Jantalia et al., 2007). The Soy Moratorium might therefore have contributed to corn expansions. Our estimates suggest that leakage to corn can account for 20% of the deforestation leakage related to non-soy crops. Specifically, the estimated elasticity of deforestation with respect to the corn price increased by 0.14. This led to 1.0 km^2 higher annual deforestation on average across the treated municipalities and a total of about 1150 km^2 in our sample (Table A.4).

These results point to a novel form of leakage related to the Soy Moratorium, which to the best of our knowledge has not been documented in the existing literature. The previous studies identify two other forms of leakage associated with this industry-driven initiative. First, high deforestation rates during the preceding years made it possible that over 90% of soybean field extension occurred on land that had been previously cleared between 2006 and 2010 (Macedo et al., 2012). Second, the Soy Moratorium comprises only the Biome of the Legal Amazon, and increasing deforestation rates in the neighbouring Cerrado biome may have been linked to the Soy Moratorium (Gibbs et al., 2010).[24]

6. Robustness checks

In this section, we present robustness checks for the results presented in Tables 3 and 4.

Alternative specifications for baseline models We first present our baseline model for the SM with a continuous treatment variable in Table A.8, and the results stay the same. We then present our baseline model with all three policies included simultaneously, in Table A.9. We find qualitatively robust and consistent results for PM and CZ. For SM, the soy and corn price results become insignificant. The main results that the SM did not change the effect of the overall price index, but did make deforestation more sensitive to non-soy prices remain robust.

In Tables A.10–A.15, we control for a large set of omitted variables, check robustness to different samples and to different specifications. As we have more limited coverage for some of the control variables, column 1 in Tables A.10–A.15 presents our baseline model on the limited sample for comparison. We investigate robustness in terms of alternative definitions of the dependent variable and geographic characteristics in Tables A.16–A.19.

Agriculture The municipalities in our sample differ in terms of how developed their agriculture sector already is, which may affect the pressure to deforest further and the implementation of the policies. In columns 2 and 3 in Tables A.10–A.15, we address this by controlling for lagged areas allocated to agriculture and for agricultural productivity. In column 4, we control for population. These controls do not affect the conclusions of this study.

Other policies The three policies we focus on in this paper may be correlated with other policy efforts implemented by Brazil, as discussed in section 2. In columns 5–9 in Tables A.10–A.15, we control for agricultural credits, given to crop production or cattle production, or the stringency of monitoring and law enforcement measured as the number of fines issued by the environmental police. If anything, our results for PM and CZ become stronger with these controls.

Furthermore, the three policies that we consider may in certain municipalities overlap with and complement each other. For example, Abman (2014) points out that international beef and soy companies withdraw from buying these commodities from municipalities with priority status, suggesting a channel through which the policy worked that is similar to the Soy Moratorium. Seeking to insulate the effect of the different policies, column 10 in Tables A.10–A.15 include the two other policies. Our results remain robust to these specifications.

Finally, column 11 in Tables A.10–A.15 presents the results where we include as control variables the area registered in CAR at the municipality level interacted with year dummies. The CAR-variable is based on the CAR-registry as published in 2016 and is time-invariant. The results are very similar to the main results.

Alternative specification In our baseline specification, we include the lagged remaining forest and its interaction with the price as control variables. The purpose is to account for heterogeneity related to the potential for deforestation and earlier development. When we exclude these controls in column 12 in Tables A.10–A.15, we obtain similar results as for the baseline. SM is now associated with lower deforestation from the overall price index, but we find no effect of SM for the soy price and the non-soy price, and a positive effect for the corn price.

Sample size Our baseline sample excludes municipalities outside of the forest frontier, or the so-called arch of deforestation (Levy et al., 2018). In column 1 in the lower panel of Tables A.10–A.15, we show that our baseline results are robust to including the other municipalities in the Brazilian Amazon for which we have the necessary data.

Could Brazil influence the world market price of soy? Throughout our study period, Brazil was the second largest soy producer in the world, with a market share of minimum 23.5% in 2002 and maximum of 29.3% in 2013 (FAO, 2018). The number one producer was the US, with a market share of 36.4% on average. The production of soy in our study area, the Brazilian Amazon, constituted only 34% of the total production of soy in Brazil in 2013. While 60% of the total soy exports of Brazil were destined for Europe in 2002, about 75% of all exports went to China in 2013 (SECEX, 2017). To deal with the concern that Brazil is large enough to influence the world market price for soy, and hence potentially violating the assumption that the world price is exogenous to events in Brazil, we run robustness checks excluding the municipalities with the largest soy production in the Brazilian Amazon in column 2 in the lower panel of Tables A.10–A.15. In our study period, those municipalities were responsible for up to 35% of the total Brazilian Amazonian soy production. In column 3, we exclude instead the 10% municipalities with the highest deforestation rates. Our results are robust to excluding either of these two types of large actors, although we loose some statistical significance for the SM in combination with the specific price indexes.

[24] The Brazilian Cerrado is another type of forest biome that covers much of Mato Grosso state. Mato Grosso in turn, is a state in the Southern part of the Amazon region, which hosts many of the large-scale farms and soybean producers.

The Global Forest Change dataset In our analysis, we use Brazil's National Space Research Institute's (INPE) data on deforestation. The Brazilian government uses these data to monitor deforestation in the Brazilian Amazon. Richards et al. (2017) argue that the decision to use these data as a policing tool has incentivized landowners to find other ways to deforest and avoid compliance with Brazil's official monitoring and enforcement system. They provide evidence of divergence between PRODES and other deforestation indicators after 2008, which implies that INPE's dataset might overestimate the impacts of the policies on deforestation. In column 6 "Hansen" in Tables A.10–A.15, we therefore use instead the Global Forest Change (GFC) dataset (Hansen et al., 2013). These data cover the entire municipalities. For comparison, we include estimates for deforestation "In zones" only in column 4 and for the "Entire" municipality in column 5. The "Entire"-column is thus comparable to the "Hansen"-column, and they show qualitatively the same effects as our baseline estimates, with two exceptions. First, the SM is found to increase forest loss related to the general commodity price index when forest loss is measured with the GFC data. Second, and consistent with the first, the SM is not found to reduce the impact of the soy price on forest loss when measured with the GFC data. These two discrepancies are consistent with the observation of Richards et al. (2017) regarding adaptation of different deforestation patterns. However, one caveat is that we do not find similar deviations for PM. Another caveat is that the robustness results for SM with the soy price in general are statistically less robust than our other results. For completeness, we note that all coefficients in the column "In zones" across Tables A.10–A.15 are statistically insignificant, which may not be surprising given that the areas within the conservation zones have seen low levels of deforestation.

Exogenous weights in the price index? As weights in the municipality specific price indexes, we use the share of agricultural land devoted to each crop. The weights need to balance two concerns. On the one hand, they need to be relevant and reflect the exposure of each municipality to the international commodity prices. On the other hand, they should be exogenous to unobserved factors determining deforestation and the policies. Our price index thus has similarities with Bartik instruments, which are created by interacting local shares (such as initial industry shares) with a national time-varying variable (such as industry growth rates). Goldsmith-Pinkham et al. (2018) highlight the importance of exogenous local weights for identification in Bartik applications. Throughout this paper, we follow Bazzi and Blattman (2014) and use the land allocations in the initial year, 2002, to make the weights pre-determined.

To scrutinize the relevance of our price index, we use the average share of the crop areas over the entire sample period as weights instead of the weights from the initial year. These weights should better reflect the actual exposure to the international prices, especially if municipalities have seen large expansions or contractions in the area allocated to different crops. The results are presented in column 7 in the lower panel of Tables A.10–A.12. Second, we use weights based on the crop area in 2005 in column 8, the year before the introduction of the SM (note that we for the soy, non-soy and corn prices always use the agricultural areas in 2005 for the weights).

To scrutinize the exogeneity of our price index, we show results for an agricultural price index weighted by potential yields (WPY) in column 9. Out of the 10 crops that we use in our baseline price index, we have the data to do this for 7 crops: Rice, Soybeans, Corn, Sugar cane, Banana, Citrus fruits and Cotton. Potential yields is a measure provided by the FAO GAEZ database, which calculates potential production based on geological and climatic conditions and is available at a pixel level. The data measure PY in kilograms per hectare for a crop in a given location and we constructed the mean PY at the municipality level by statistical zoning in QGIS. To create a sample-wide reference point for crop *j*, we calculated the mean PY across all municipalities: $PY_j = \sum_{i=1}^{N} PY_j/N$. We then calculated the relative PY for crop *j* in each municipality *i*: $rPY_{ij} = PY_{ij}/PY_j$. rPY_{ij} reflects the productivity of the soil in municipality *i* in producing crop *j*, relative to the average of the Brazilian Amazon. We use *rPY* as the weights in the price index, which for municipality *i* over all crops *j* can be expressed as: $P_{PY,it} = \sum_j rPY_{ij} {}^* P_{jt}$, where P_{jt} is our standard price from the world bank (set to 1 in 2000). As we use the log of the price index in the regressions, it does not matter that the weights do not necessarily sum to one.

Across all these three alternative weighing schemes, our results remain qualitatively and quantitatively stable (see columns 7–9 in Tables A.10–A.12). Again, the notable exception is the Soy Moratorium, for which the triple interaction takes a negative coefficient in all three cases but is (marginally) statistically significant only with Potential Yield weights.

Spatial correlation In our baseline specification, we cluster the standard errors at the municipality level to deal with serial correlation. In addition, there might be spatial correlation across neighbouring municipalities.[25] We follow Cameron et al. (2011) and use two-way clustered standard errors (on municipality and state-year) in the second most right column in the lower panel of Tables A.10-–A.15. In the most right column, we include instead state-year fixed effects as control variables. These robustness test do not change the conclusions of this study, although the triple interaction for the Soy Moratorium loses statistical significance for some of the separate price regressions.

Controlling for geographical characteristics. In our setting, characteristics that affect the profitability of agriculture may affect both the pressure to deforest and where the government choose to implement the policies. To test whether our triple-difference estimates pick up the effects of geographic characteristics that may affect the profitability of agriculture, we include interactions between the prices and the following five geographic characteristics: *nutrient*(1) concentration refers to soil fertility that is particularly important for low input farming; *nutrient*(2) concentration is particularly relevant for the effectiveness of fertiliser application; *oxygen* availability in the soil is particularly important for root development; *root* refers to soil volume limitations of a soil unit, affecting penetration and constraining yield formation; and *access* provides the estimated travel time to the nearest city with 50,000 or more inhabitants and plausibly also accounts for transportation costs. Tables A.18 and A.19

[25] Municipalities within a Brazilian state do not only share geographical proximity but also political, legislative and cultural commonalities.

Table 5
Carbon loss.

	Carbon loss			
	(1) Price	(2) PM	(3) SM	(4) CZ
TreatGr x Active × L.Price		−1.274**	0.025	0.167***
		(0.617)	(0.041)	(0.034)
L.Initial × L.Price	−0.256***	−0.243***	−0.245***	−0.330***
	(0.022)	(0.024)	(0.022)	(0.024)
L.Initial	2.711***	2.675***	2.993***	2.539***
	(0.175)	(0.174)	(0.186)	(0.181)
Observations	5170	5170	5170	5170
Municipalities	470	470	470	470
R-sq	0.46	0.47	0.49	0.48
I x P	Yes	Yes	Yes	Yes
Total price effects, policy off/on				
dydx(P) policy off	0.93	3.63	0.14	0.45
p-quant	0.00	0.00	0.69	0.19
dydx(P) policy on		2.35	0.34	1.40
p-quant		0.02	0.35	0.00
Difference in total price effect				
Difference		−1.27	0.21	0.95
p-quant		0.04	0.54	0.00

Note: Dependent variable is log carbon loss in areas outside of conservation zones. Column 1 is based on equation (2) and includes interactions between the price and year dummies as well as interactions between the policy dummy and year dummies. Columns 2–4 are based on equation Eqn 3 and include interactions between the price and year dummies as well as interactions between the policy dummy and year dummies. All columns include municipal and year fixed effects and the standard errors shown in parentheses are clustered on the municipality level. Section 3.1 explains the carbon data.

present the results for the models in Tables 3 and 4, respectively. We conclude that our results are robust and do not reflect variation in these geographic characteristics.

7. The implicit price of carbon

To calculate the implicit price of carbon in our setting, we compare the value of a hectare of forest in terms of carbon storage against the alternative value of the hectare of land in agricultural crop production. The implicit price will simply be the ratio of present value agricultural profit to carbon density.[26]

For agricultural profits, we start out with the observed revenue from crop production per hectare, R/ha, measured in 2020-USD. We assume a 15% profit margin and a 10% discount rate. We need the latter to calculate the present value, as it is the value over the life time of the plot that matters.[27]

To get at the relevant carbon density, we obtain estimates of the effect of prices and policies on carbon emissions. Table 5 presents estimates of our baseline models, equation (2) and equation (3), with carbon loss as the dependent variable. There is a difference between carbon and forest, simply because the forest varies in terms of carbon density across municipalities.[28] We find similar effects as for deforestation being the dependent variable. In column 1, we estimate that a one percent increase in the general price index increases carbon loss by 0.93 percent. In columns 2–4, we find that PM reduces the price effect, CZ amplifies the price effect and SM makes no difference on the overall price effect.

By combining our estimates for deforestation and carbon, we can obtain an estimate of the carbon density of the affected forest. For deforestation, we found 35.4 km^2 saved forest loss per municipality due to PM (Table A.4). The corresponding estimate of the value of CO_2 measured at 50 USD/tCO_2 is 78 million USD. Combining the two, yields a value in terms of CO_2 of USD 22,000 per hectare. For the SM and CZ policies, the corresponding figures are USD 18,000 and USD 24,000, respectively. For reference, the mean and median in our raw data for year 2000 are USD 17,000 and USD 20,000.

[26] $P_{CO_2} = \frac{\textit{Present value agricultural profits per hectare}}{CO_2 \textit{ density per hectare}}$

[27] As an example, our data suggest a yield of about 3 tonne soy per hectare per year and a price of about 400 USD per tonne. The present values are then 12,000 USD of the revenues $(3 \times 400/0.10)$ and 1800 USD of the profits $(12,000 \times 0.15)$. See Busch and Engelmann (2017) and the discussion in the Appendix regarding our assumptions.

[28] See section 3 for more details on the carbon data. For simplicity, we have measured carbon density in dollars, valued at 50 USD per tonne of CO_2 in 2020-USD.

For PM, the implied price of CO_2-emissions, P_{CO_2}, is 6.2 USD/tCO_2.[29] In other words, this is the amount needed to make a farmer indifferent between this size of payment or clearance. The figures derived from the SM and CZ policies are 6.2 USD/tCO_2 and 6.7 USD/tCO_2, respectively.[30]

Our stylized calculations are informative on the cost of avoided deforestation as an abatement technology. Our figures of about 6.5 USD per tonne of CO_2 are lower than some of the values in the literature. Busch and Engelmann (2017) report figures on agricultural revenue, forest loss and carbon density from which we can back out an average shadow value of 11 USD per tonne of CO_2 for Latin America over 2001–2012, when CO_2 is valued at USD 50 per tonne.[31] Using integrated assessment modelling and quantifying the economic opportunity cost of deforestation in terms of lost crop production value, Overmars et al. (2014) find that the price per tonne CO_2 saved via avoided deforestation is between USD 2 and 9 per tonne in Central and South America and between 20 and 60 USD per tonne in Southeast Asia (on average, over the 2005–2030 period).[32] Using detailed panel data on land use and the stock of carbon in the Brazilian Amazon together with dynamic discrete choice modelling, Araujo et al. (2020) find that a perceived value of USD 7.3 per tonne of CO_2 can rationalize farmers' land use decisions. They use a 5% discount rate. Gillingham and Stock (2018) report costs of different abatement policies based on a compilation of economic studies. The costs show huge variation, with reforestation at 1–10 2017-USD/tCO_2 and reducing federal coal leasing at 33–68 2017-USD/tCO_2, as two examples. Compared to their list, our calculations suggest that reducing deforestation in Brazil may be a cheap alternative.

Our stylized calculation rests on the assumption that the observed R/ha is a good proxy for the counterfactual R/ha, i.e. what would have been the revenue per hectare in the treated municipalities if the policy had not been implemented. If the policies affect the opportunity cost, then the R/ha in the treated municipalities may not be a good proxy for the counterfactual opportunity cost. Our measure of opportunity cost rests on strong assumptions. A more precise quantification of the counterfactual opportunity cost requires a richer analysis of agricultural production, which we regard to be beyond the scope of our stylized calculation.[33] Table A.20 presents summary statistics for R/ha for the treatment and control groups, before and after the policies were implemented. The upper row of Fig. A.1 presents the development of R/ha over time for the control and treatment groups. For all three policies, R/ha in the two groups follow each other closely throughout the period. The two lower rows of Fig. A.1 present the distributions of R/ha in the control and treatment groups before and after the three policies where implemented. The shape of the distributions appear similar before and after the policies were implemented. Although we cannot rule out that the policies have affected our measure of opportunity cost, the presented descriptive statistics suggest that the opportunity costs have not shifted dramatically due to the policies. As a 1% change in R/ha translates to a 1% change in our implicit prices, it is easy to recalculate them for alternative values of R/ha. Based on Fig. A.1, the relevant band of R/ha in our data is 500–3000 USD/ha.

Our stylized calculations shed light on to which extent the cost of cutting CO_2-emissions by reducing deforestation has been harmonized across space in Brazil. Our figures suggest remarkably similar carbon prices across the three policies. Both the carbon density and the actual value creation per hectare are behind these results. The same marginal costs everywhere may be indicative of cost efficiency; cost-minimizing agents would reduce emissions where it is cheapest to do so, until marginal costs are harmonized. Assuncao et al. (2019b) study optimal counterfactual targeting of municipalities under the PM-policy, given that the authorities aim at minimizing deforestation subject to a monitoring resource constraint. They consider constraints in terms of either the total area that can be monitored or the total number of municipalities that can be on the list. The forgone economic value of protecting a given stock of carbon should also be considered by the authorities to achieve economic efficiency.

Given the stylized nature of our calculations, the resulting implicit carbon price should be used with caution. We leave it to future research to evaluate the broader economic effects of deforestation, which will help in establishing the actual abatement costs of reduced deforestation.

8. Conclusion

Agricultural commodity prices may be high in the coming decades as growth in crop yields may stagnate due to climate change (Iizumi et al., 2017; Wiebe et al., 2015), as the use of land regulation policies may increase (Harstad and Mideksa, 2017), and as the world's population and incomes will increase (FAO, 2017). In this paper, we investigated the effectiveness of two

[29] For the calculation of the implicit CO_2-price, we consider the estimated carbon loss for one year. This is conceptually comparable to the present value of agricultural profits. Emission of the carbon stock already stored in forest is a one time emission. As discussed in section 3, we ignore carbon sequestration, i.e. the carbon the forest could have sinked if it were kept standing, as it accounts for less than 0.5% of the carbon stock per year.

[30] Based on the ten crops included in this study, the mean value of crop production per hectare are for the treated groups in the treated years as follows: 1,812 *USD/ha* (PM); 1,509 *USD/ha* (SM); 2,123 *USD/ha* (CZ). If we use PM as an example, the present value of land profits with a 15% profit margin and a 10% discount rate is 2,718 *USD/ha* ((1,812 *USD/ha*)/0.10∗0.15). The carbon density in the PM-case is 440 tCO_2/ha ((22,000 *USD/ha*)/(50 USD/tCO_2)). The resulting implicit price of carbon is $P_{CO_2} = (2,718\ USD/ha)/(440\ tCO_2/ha) = 6.2\ USD/tCO_2$. This is based on the assumption that the entire estimated deforested area is used for overall crop production. We follow the same procedure for the other policies. Table A.21 presents the numbers.

[31] Busch and Engelmann (2017) report potential agricultural revenue of USD 2978 per hectare per year in Latin America. With a profit margin of 15% and a 10% discount rate, this amounts to a present value of about USD 4500 per hectare. In their estimates, 49.2 million hectare deforestation correspond to 19.2 Giga tonnes of CO_2-emissions in Latin America over 2001–2012. This results in about 11 USD per tonne of CO_2: $49.2 \times 10^6 \times 4467/(19.2 \times 10^9) = 11.4$. Their carbon emissions per hectare of forest corresponds to about USD 19,500 when valued at USD 50 per tonne of CO_2.

[32] Kindermann et al. (2008) also find that the cost of reducing emissions through avoided deforestation is lowest in Africa and highest in South East Asia, with Central and South America in between. They find that avoiding deforestation can be cost effective compared to other abatement technologies.

[33] We discuss our measure of opportunity cost in the appendix.

command-and-control policies and one market-based policy in protecting tropical forests confronted with higher agricultural commodity prices. We studied the Brazilian Legal Amazon, part of the world's largest tropical rainforest and a key supplier of agriculture commodities such as soy and corn to the world market. Our results showed that protection of specific areas (conservation zones) and targeting of a specific crop (Soy Moratorium) induce leakages within municipalities. Prioritizing entire municipalities in monitoring and law enforcement efforts (blacklisting) is, in contrast, effective in reducing deforestation related to international agricultural commodity prices. We illustrated the implicit carbon price in our setting, using data on crop production values and carbon loss.

Our analysis sheds light on the challenge of avoiding conversion from forests to agricultural production. Our results indicate that countries need broad-ranging policies to achieve a fully sustainable agricultural production. Each policy, however, is associated with its own pros and cons and thus future analysis could investigate the intricate links between deforestation and economic development. This could help local and international policy makers to weight deforestation against other abatement policies. It could also help in designing policies to dampen the negative local economic effects of reduced deforestation or to compensate local stakeholders through transfers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102452.

References

Abman, R., 2014. Reelection Incentives, Blacklisting and Deforestation in brazil. University of California Santa Barbara. Mimeo.
Alexandratos, N., 2008. Food price surges: possible causes, past experience, and longer term relevance. Popul. Dev. Rev. 34 (4), 663–697.
Alix-Garcia, J., 2007. A spatial analysis of common property deforestation. J. Environ. Econ. Manag. 53 (2), 141–157.
Alix-Garcia, J.M., Sims, K.R.E., Yanez-Pagans, P., 2015. Only one tree from each seed? environmental effectiveness and poverty alleviation in Mexico's payments for ecosystem services program. Am. Econ. J. Econ. Pol. 7 (4), 1–40.
Anderson, L.O., Martino, S.D., Harding, T., Kuralbayeva, K., Lima, A., 2016. The effects of land use regulation on deforestation: evidence from the brazilian amazon. OxCarre Working Papers 172.
Andrade, L., Chagas, A.L.S., 2016. Spillover Effects of Blacklisting Policy in the Brazilian Amazon. University of Sao Paulo. working paper No. 2016-32.
Araujo, R., Costa, F., Sant'Anna, M., 2020. Efficient Forestation in the Brazilian Amazon: Evidence from a Dynamic Model.
Arima, E., Barreto, P., Araujo, E., Soares-Filho, B., 2014. Public policies can reduce tropical deforestation: lessons and challenges from Brazil. Land Use Pol. 41, 465–473.
Assunção, J., Gandour, C., Rocha, R., 2015. Deforestation slowdown in the legal amazon: prices or policies? Environ. Dev. Econ. 20 (6), 697–722.
Assunção, J., Gandour, C., Rocha, R., 2017. Detering Deforestation in the Amazon: Environmental Monitoring and Law Enforcement. *CPI Working paper*, Climate Policy Initiative.
Assunção, J., Gandour, C., Rocha, R., Rocha, R., 2019a. The effect of rural credit on deforestation: evidence from the brazilian amazon. Econ. J. (page forthcoming).
Assunção, J., McMillan, R., Murphy, J., Souza-Rodrigues, E., 2019b. Optimal Environmental Targeting in the Amazon Rainforest. NBER Working paper 25636.
Aukland, L., Costa, P.M., Brown, S., 2003. A conceptual framework and its application for addressing leakage: the case of avoided deforestation. Clim. Pol. 3 (2), 123–136.
Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A., 2017. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science 358 (6360), 230–234.
Barbier, E.B., Burgess, J.C., 2001. The economics of tropical deforestation. J. Econ. Surv. 15 (3), 413–433.
Bazzi, S., Blattman, C., 2014. Economic shocks and conflict. Am. Econ. J. Macroecon. 6, 1–38.
Burgess, R., Costa, F.J.M., Olken, B., 2017. The Power of the State: National Borders and the Deforestation of the Amazon. (unpublished manuscript).
Burgess, R., Hansen, M., Olken, B.A., Potapov, P., Sieber, S., 2012. The political economy of deforestation in the tropics. Q. J. Econ. 127 (4), 1707–1754.
Busch, J., Engelmann, J., 2017. Cost-effectiveness of reducing emissions from tropical deforestation, 2016–2050. Environ. Res. Lett. 13 (1), 015001.
Cameron, A.C., Gelbach, J.B., Miller, D.L., 2011. Robust inference with multiway clustering. J. Bus. Econ. Stat. 29 (2), 238–249.
Chomitz, K.M., Thomas, T.S., 2003. Determinants of land use in amazonia: a fine-scale spatial analysis. Am. J. Agric. Econ. 85 (4), 1016–1028.
Cust, J., Harding, T., Vézina, P.-L., 2019. Dutch disease resistance: evidence from Indonesian firms. Journal of the Association of Environmental and Resource Economists 6 (6), 1205–1237.
De Sá, S.A., Palmer, C., Di Falco, S., 2013. Dynamics of indirect land-use change: empirical evidence from Brazil. J. Environ. Econ. Manag. 65 (3), 377–393.
Deaton, A., Miller, R.I., et al., 1995. International Commodity Prices, Macroeconomic Performance, and Politics in Sub-saharan Africa. International Finance Section, Department of Economics, Princeton University.
Drechsel, T., Tenreyro, S., 2018. Commodity booms and busts in emerging economies. J. Int. Econ. 112, 200–218.
Dube, O., Vargas, J., 2013. Commodity price shocks and civil conflict: evidence from Colombia. Rev. Econ. Stud. 80, 1384–1421.
e. a. Edenhofer, O., Pichs-Madruga, R., Sokona, Y., 2014. Climate Change 2014: Mitigation of Climate Change: Contribution of Working Group Iii to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK/NY.
FAO, 2017. The Future of Food and Agriculture–Trends and Challenges.
FAO, 2018. FAO STAT. Available at: www.fao.org/faostat, (Accessed 0 December 2018).
Fearnside, P.M., 2001. Land-Tenure Issues as Factors in Environmental Destruction in Brazilian Amazonia, vol. 29, pp. 1361–1372.
Fernández, A., Schmitt-Grohé, S., Uribe, M., 2017. World shocks, world prices, and business cycles: an empirical investigation. J. Int. Econ. 108, S2–S14.
Foster, A.D., Rosenzweig, M.R., 2003. Economic growth and the rise of forests. Q. J. Econ. 118 (2), 601–637.
Gibbs, H.K., Munger, J., L'Roe, J., Barreto, P., Pereira, R., Christie, M., Amaral, T., Walker, N.F., 2016. Did ranchers and slaughterhouses respond to zero-deforestation agreements in the brazilian amazon? Conservation Letters 9 (1), 32–42.
Gibbs, H.K., Rausch, L., Munger, J., Schelly, I., Morton, D.C., Noojipady, P., Soares-Filho, B., Barreto, P., Micol, L., Walker, N.F., 2015. Brazil's soy moratorium. Science 347 (6220), 377–378.
Gibbs, H.K., Ruesch, A.S., Achard, F., Clayton, M.K., Holmgren, P., Ramankutty, N., Foley, J.A., 2010. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. Proc. Natl. Acad. Sci. Unit. States Am. 107, 16732–16737.
Gillingham, K., Stock, J.H., 2018. The cost of reducing greenhouse gas emissions. J. Econ. Perspect. 32 (4), 53–72.
Goldsmith-Pinkham, P., Sorkin, I., Swift, H., 2018. Bartik Instruments: what, when, Why, and How. NBER Working Papers 24408. National Bureau of Economic Research, Inc.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (6160), 850–853.
Harding, T., Venables, A.J., 2016. The implications of natural resource exports for nonresource trade. IMF Econ. Rev. 64 (2), 268–302.
Hargrave, J., Kis-Katos, K., 2013. Economic causes of deforestation in the Brazilian Amazon: a panel data analysis for the 2000s. Environ. Resour. Econ. 54, 471–494.
Harstad, B., Mideksa, T.K., 2017. Conservation contracts and political regimes. Rev. Econ. Stud. 84 (4), 1708–1734.
Howard, P.H., Sylvan, D., 2015. The Economic Climate: Establishing Expert Consensus on the Economics of Climate Change. Institute for Policy Integrity, pp. 438–441.
Hubau, W., Lewis, S.L., Phillips, O.L., Affum-Baffoe, K., Beeckman, H., Cuní-Sanchez, A., Daniels, A.K., Ewango, C.E.N., Fauset, S., Mukinzi, J.M., Sheil, D., Sonké, B., Sullivan, M.J.P., Sunderland, T.C.H., Taedoumg, H., Thomas, S.C., White, L.J.T., Abernethy, K.A., Adu-Bredu, S., Amani, C.A., Baker, T.R., Banin, L.F., Baya, F., Begne, S.K., Bennett, A.C., Benedet, F., Bitariho, R., Bocko, Y.E., Boeckx, P., Boundja, P., Brienen, R.J.W., Brncic, T., Chezeaux, E., Chuyong, G.B., Clark, C.J., Collins, M., Comiskey, J.A., Coomes, D.A., Dargie, G.C., de Haulleville, T., Kamdem, M.N.D., Doucet, J.-L., Esquivel-Muelbert, A., Feldpausch, T.R., Fofanah, A., Foli, E.G., Gilpin, M., Gloor, E., Gonmadje, C., Gourlet-Fleury, S., Hall, J.S., Hamilton, A.C., Harris, D.J., Hart, T.B., Hockemba, M.B.N., Hladik, A., Ifo, S.A., Jeffery, K.J., Jucker, T., Yakusu, E.K., Kearsley, E., Kenfack, D., Koch, A., Leal, M.E., Levesley, A., Lindsell, J.A., Lisingo, J., Lopez-Gonzalez, G., Lovett, J.C., Makana, J.-R., Malhi, Y., Marshall, A.R., Martin, J., Martin, E.H., Mbayu, F.M., Medjibe, V.P., Mihindou, V., Mitchard, E.T.A., Moore, S., Munishi, P.K.T., Bengone, N.N., Ojo, L., Ondo, F.E., Peh, K.S.-H., Pickavance, G.C., Poulsen, A.D., Poulsen, J.R., Qie, L., Reitsma, J., Rovero, F., Swaine, M.D., Talbot, J., Taplin, J., Taylor, D.M., Thomas, D.W., Toirambe, B., Mukendi, J.T., Tuagben, D., Umunay, P.M., van der Heijden, G.M.F., Verbeeck, H., Vleminckx, J., Willcock, S., Wöll, H., Woods, J.T., Zemagho, L., 2020. Asynchronous carbon sink saturation in African and Amazonian tropical forests. Nature 579 (7797), 80–87.
IBGE, 2017. Sistema IBGE de Recuperação automática. Available at; https://sidra.ibge.gov.br/home/pms/brasil, (Accessed 10 October 2016).
Iizumi, T., Furuya, J., Shen, Z., Kim, W., Okada, M., Fujimori, S., Hasegawa, T., Nishimori, M., 2017. Responses of crop yield growth to global temperature and socioeconomic changes. Sci. Rep. 7 (1).
INPE, 2015. ProjectoProdes - monitoriamento da foresta Amazônica Brasileira por satéllite.
Jantalia, C.P., Resck, D.V., Alves, B.J., Zotarelli, L., Urquiaga, S., Boddey, R.M., 2007. Tillage effect on C stocks of a clayey Oxisol under a soybean-based crop rotation in the Brazilian Cerrado region. 95, 97–109.
Karstensen, J., Peters, G.P., Andrew, R.M., 2013. Attribution of CO 2 emissions from Brazilian deforestation to consumers between 1990 and 2010. Environ. Res. Lett. 8 024005.
Kindermann, G., Obersteiner, M., Sohngen, B., Sathaye, J., Andrasko, K., Rametsteiner, E., Schlamadinger, B., Wunder, S., Beach, R., 2008. Global cost estimates of reducing carbon emissions through avoided deforestation. Proc. Natl. Acad. Sci. Unit. States Am. 105 (30), 10302–10307.
Kissinger, G., Herold, M., De Sy, V., 2012. Drivers of Deforestation and Forest Degradation: a Synthesis Report for Redd+ Policymakers. Lexeme Consulting. Technical report.
Koch, N., Ermgassen, E.K.H.J., Wehkamp, J., Oliveira, F., Schwerhoff, G., 2018. Agricultural Productivity and Forest Conservation: Evidence from the Brazilian Amazon. Universty of Cambridge. Working paper.
Lawson, S., 2014. Consumer goods and deforestation. Available at; https://www.forest-trends.org/publications/consumer-goods-and-deforestation/, (Accessed 0 November 2018).
Le Quéré, C., Andrew, R., Canadell, J.G., Sitch, S., Korsbakken, J.I., Peters, G.P., Manning, A.C., Boden, T.A., Tans, P.P., Houghton, R.A., et al., 2016. Global Carbon Budget 2016.
Levy, M., Lopes, A.V., Cohn, A., Larsen, L.G., Thompson, S.E., 2018. Land use change increases streamflow across the arc of deforestation in Brazil. Geophys. Res. Lett. 45, 3520–3530.
Lopez, R., Galinato, G.I., 2005. Trade policies, economic growth, and the direct causes of deforestation. Land Econ. 81, 145–169.
Macedo, M.N., DeFries, R.S., Morton, D.C., Stickler, C.M., Galford, G.L., Shimabukuro, Y.E., 2012. Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. In: Proceedings of the National Academy of Sciences of the United States of America, vol. 109. U.S. Gov't, Non-P.H.S, pp. 1341–1346. Historical Article Journal Article Research Support, Non-U.S. Gov't Research Support.
Martinelli, L.A., Filoso, S., 2008. Expansion of sugarcane ethanol production in Brazil. Ecol. Appl. 18, 885–898.
Mitchard, E.T., 2018. The tropical forest carbon cycle and climate change. Nature 559 (7715), 527–534.
Mitchell, D., 2008. A Note on Rising Food Prices. The World Bank. Policy Research Working Paper Series 4682.
MMA, 2017. Ministério do Meio Ambiente. Availabe at; http://mapas.mma.gov.br/i3geo/datadownload.htm, (Accessed 13 February 2017).
Muralidharan, K., Prakash, N., 2017. Cycling to school: increasing secondary school enrollment for girls in India. Am. Econ. J. Appl. Econ. 9 (3), 321–350.
Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., Seroa da Motta, R., Armijo, E., Castello, L., Brando, P., Hansen, M.C., McGrath-Horn, M., Carvalho, O., Hess, L., 2014. Slowing Amazon Deforestation through Public Policy and Interventions in Beef and Soy Supply Chains, vol. 344. U.S. Gov't, Non-P.H.S. Review, pp. 1118–1123. Journal Article Research Support, Non-U.S. Gov't Research Support.
Nolte, C., Agrawal, A., Silvius, K.M., Soares-Filho, B.S., 2013. Governance regime and location influence avoided deforestation success of protected areas in the brazilian amazon. Proc. Natl. Acad. Sci. Unit. States Am. 110 (13), 4956–4961.
Overmars, K.P., Stehfest, E., Tabeau, A., van Meijl, H., Beltrán, A.M., Kram, T., 2014. Estimating the opportunity costs of reducing carbon dioxide emissions via avoided deforestation, using integrated assessment modelling. Land Use Pol. 41, 45–60.
Pfaff, A., Robalino, J., 2017. Spillovers from conservation programs. Annual Review of Resource Economics 9, 6.1–6.17.
Pfaff, A., Robalino, J., Lima, E., Sandoval, C., Herrera, L.D., 2014. Governance, location and avoided deforestation from protected areas: greater restrictions can have lower impact, due to differences in location. World Dev. 55, 7–20.
Pfaff, A.S., 1999. What drives deforestation in the brazilian amazon?: evidence from satellite and socioeconomic data. J. Environ. Econ. Manag. 37 (1), 26–43.
Richards, P., Arima, E., VanWey, L., Cohn, A., Bhattarai, N., 2017. Are Brazil's deforesters avoiding detection? Conservation Letters 10 (4), 470–476.
Rodrigue, J., Soumonni, O., 2014. Deforestation, foreign demand and export dynamics in Indonesia. J. Int. Econ. 93 (2), 316–338.
Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Global Environ. Change 15 (1), 23–31.
Saatchi, S.S., Houghton, R.A., dos Santos Alvalá, R.C., Soares, J.V., Yu, Y., 2007. Distribution of aboveground live biomass in the amazon basin. Global Change Biol. 13 (4), 816–837.
SECEX, 2017. Secretaria de Comércio exterior. Available at: dataviva.info, (Accessed 0 October 2017).
Soares-Filho, B., Moutinho, P., Nepstad, D., Anderson, A., Rodrigues, H., Garcia, R., Dietzsch, L., Merry, F., Bowman, M., Hissa, L., Silvestrini, R., Maretti, C., 2010. Role of brazilian amazon protected areas in climate change mitigation. Proc. Natl. Acad. Sci. Unit. States Am. 107 (24), 10821–10826.
Soares-Filho, B., Rajão, R., Macedo, M., Carneiro, A., Costa, W., Coe, M., Rodrigues, H., Alencar, A., 2014. Cracking Brazil's forest code. Science 344 (6182), 363–364.
Stiglitz, J.E., Stern, N., Duan, M., Edenhofer, O., Giraud, G., Heal, G.M., la Rovere, E.L., Morris, A., Moyer, E., Pangestu, M., et al., 2017. Report of the High-Level Commission on Carbon Prices.
Svahn, J., Brunner, D., 2018. Did the Soy Moratorium Reduce Deforestation in the Brazailian Amazon?. Masters dissertation. Department of Economics, Norwegian School of Economics.
Verissimo, A., Rolla, A., Vedoveto, M., de Melo Futada, S., 2011. Protected Areas in the Brazilian Amazon: Challenges and Opportunities. Imazon/ISA.
Wiebe, K., Lotze-Campen, H., Sands, R., Tabeau, A., van der Mensbrugghe, D., Biewald, A., Bodirsky, B., Islam, S., Kavallari, A., Mason-DCroz, D., Muller, C., Popp, A., Robertson, R., Robinson, S., van Meijl, H., Willenbockel, D., 2015. Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios. Environ. Res. Lett. 10 (8), 085010.

Further reading

Nauclér, T., Enkvist, P.-A., 2009. Pathways to a low-carbon economy: version 2 of the global greenhouse gas abatement cost curve. McKinsey & Company 192 (3).