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Public policies can reduce tropical deforestation: Lessons and challenges from Brazil

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ABSTRACT

Reducing carbon emissions from deforestation and forest degradation now constitutes an important strategy for mitigating climate change, particularly in developing countries with large forests. Given growing concerns about global climate change, it is all the more important to identify cases in which economic growth has not sparked excessive forest clearance. We address the recent reduction of deforestation rates in the Brazilian Amazon by conducting a statistical analysis to ascertain if different levels of environmental enforcement between two groups of municipalities had any impact on this reduction. Our analysis shows that these targeted, heightened enforcement efforts avoided as much as 10,653 km^2 of deforestation, which translates into 1.44×10^{-1} Pg C in avoided emissions for the 3 y period. Moreover, most of the carbon loss and land conversion would have occurred at the expense of closed moist forests. Although such results are encouraging, we caution that significant challenges remain for Brazil's continued success in this regard, given recent changes in the forestry code, ongoing massive investments in hydro power generation, reductions of established protected areas, and growing demand for agricultural products.

Introduction

Although tropical deforestation and degradation have long been a concern of the academic community and the general public for a wide variety of reasons, attention has begun to focus increasingly on carbon emissions because of their contribution to global warming (Myers et al., 2000; Wright, 2005). Land use changes for 2000–2007, primarily tropical deforestation, account for an estimated 1.10 ± 0.70 Pg C y^{-1}, or 14–20% of global greenhouse gas emissions (Pan et al., 2011), and will probably remain substantial in coming decades (Sitch et al., 2005). As a consequence, the United Nations has spear-headed an initiative to reduce emissions from deforestation and forest degradation (REDD), and numerous efforts are underway worldwide to achieve such forest-based reductions. Countries like Norway have donated millions of dollars to support REDD+ forest conservation projects, which altogether now account for 9% of voluntary carbon offsets (BNDES, 2013; Peters-Stanley and Hamilton, 2012).

Given growing investment in REDD/REDD+ activities, and their importance to climate change mitigation, it is important to identify situations where REDD-oriented policies appear to be successful but not at the expense of human welfare. That said, developing sustainable relationships between natural and human systems are not easily achieved, and successful cases are few and far between (Nunes et al., 2012). Brazil, which made deforestation reduction a central piece of its climate change policy in 2009 (Brasil, 2009), appears to present one such success story. Thus, the article's objective is to examine the impact of recent environmental policy applications in Brazil, in the interest of finding a pathway to sustainable development for countries with large extents of native vegetation.

The article pursues its objective as follows. First, it considers deforestation rates in the Brazilian Amazon over the past several decades, and addresses the relationship between agricultural expansion in the basin and changes in forest area. Second, it gives an overview of environmental policy directed at Brazil's northern region, particularly its Amazonian Biome, the closed moist forest ecosystem that once covered ~4,000,000 km^2. Next, the article presents statistical analyses that reveal the extent to which

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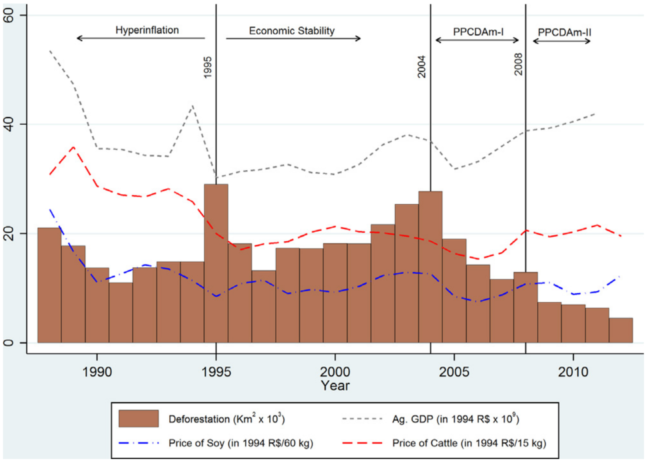

Fig. 1. Amazonian deforestation rates, price of soy, price of cattle, and agricultural GDP from 1988 to 2012, Brazil.
Sources: IEA, SP and IBGE.

recent policy measures have reduced Amazonian deforestation. It also translates these statistical results into carbon reduction values, and into ecosystem specific magnitudes of conservation. The article concludes with a brief discussion of implications of the findings for sustainable development both in Brazil and other tropical countries with valuable forest resources.

Background

Deforestation trends and agriculture

Since 1988, when Brazil's Space Agency (INPE) began monitoring Amazonian deforestation with satellite imagery, deforestation rates have varied from a record high of 29,059 km^2 in 1995 to a low of 4571 km^2 in 2012 (Fig. 1). After 2004, when 27,772 km^2 were deforested, rates have tended to decline. The sharpest percent drop occurred between 2008 and 2009, when annual forest loss plummeted from 12,911 km^2 to 7464 km^2. Given that the global economy entered serious recession in 2008, this drop might be explained by declining demand for Brazilian agricultural commodities (Walker, 2011). This is a reasonable conjecture, given the role that agriculture has played in Amazonian forest loss, particularly ranching. Planted and abandoned pastures account for 80% of all cleared lands, and annual crops, mostly soybeans, another 5% (EMBRAPA and INPE, 2011).

An alternative explanation resides in effective policy, following Brazil's recent adherence to principles of the UN-REDD program in 2009. That low rates of deforestation persisted after the recession, which ended in 2009, appears consistent with a policy-based explanation for the decline in forest loss. Correlations between deforestation and the agricultural sector are high starting with monetary reform and macroeconomic stability in 1994 and Brazil's entry into world markets as a major supplier of soybeans and beef. From 1995 until 2007, deforestation correlates with lagged soybean ($r = 0.721$) and cattle prices ($r = 0.720$), which together explain more than 75% of the total variation in rates of forest loss for the period 1995–2007. Such relationships weaken considerably after 2007. Although deforestation rates remain positively related to soybean prices for the period 2008–2011, they decouple from cattle prices, and actually reverse for agricultural GDP, with a strong negative relationship.

Thus, the decline in Brazil's deforestation rate possesses two possible explanations, namely the stagnation in global demand for agricultural goods, or the enforcement of an effective policy regime. The goal of the article is to resolve this issue, and to measure the effectiveness of a specific policy instrument that was brought to bear on the Brazil's portion of the Amazon Basin during the millennial decade.

Policy context

The institutional background. Before proceeding, we briefly consider the policy concept that motivates the article. In this regard, we take a broadly institutional perspective, with policy encompassing both explicit legislation and government programs aimed at achieving specific outcomes, typically through the promotion of positive incentives (Jepson, 2006). Also included are actions by government that produce positive environmental externalities, such as the creation of indigenous reserves. Finally, we take policy enforcement to be part of our conceptual picture, in which case the social resources (e.g. power) capable of applying law or implementing programs form part of a policy *regime*. For the Brazilian case, environmental policy germane to this article originates with the first forestry code in 1934 (Simmons, 2002), although explicit concern for the Amazonian Biome only emerged with federal highway construction in the 1970s. As the Brazilian federal government transitioned from a military regime to democracy in the mid-1980s, awareness grows both in Brazil and internationally that Amazonian forest loss, while allowing for economic development, also presented a number of environmental harms. The timing of this awareness was fortuitous given the political transition to democracy and associated institutional changes including a free press, the emergence of a politically independent judiciary, and the elaboration of human rights that included the right to sustain indigenous identities (Simmons, 2002).

Amazonian environmental policy originating in the 1980s has involved protected areas, including indigenous territories and conservation units, and modifications of the forestry code in response to the Amazonian situation. Up until the 1988 Constitution, Brazil followed an assimilation policy vis-à-vis its substantial native population, which anticipated the ultimate disappearance of native cultures and their gradual absorption into Brazilian society. The declaration of indigenous rights opened the door to territorial reserves that now cover ~20% of the land within Amazonia Legal (AML), or "The Legal Amazon." This is matched and even exceeded by lands now under some form of environmental protection by both federal and state governments that comprise ~25% of AML (Walker et al., 2009). Adaptations to the forestry code for Amazonia in 1965 increased the amount of land ranchers and farmers were required to keep as a forest reserve from 20 to 50% (Simmons, 2002). In 1996, Brazil's Space Agency, INPE, announced the largest deforestation magnitude in history, with 29,000 km^2 of the forest lost in 1995. President Fernando Henrique Cardoso took executive action and increased the forest reserve to 80%, a number that remains in place with the recently approved forestry code, although exemptions from reforesting previously deforested areas were granted depending on the size of the property and the year that deforestation occurred.

Recent policy intensifications

Although the record high deforestation rate in 1995 was followed by two years of decline (1996–1997), the trend reversed and deforestation increased consistently for the period 1998–2004, returning to the high levels of the mid-1990s. This prompted the federal government's first Action Plan to Prevent and Control Deforestation in the Amazon (PPCDAm-I), implemented between 2004 and 2007. Under this plan, Brazil's environmental enforcement agency (IBAMA) was restructured and began using INPE's 'real time' deforestation detection (DETER) to target its enforcement efforts in the field (Abdala, 2008). Another important component of the

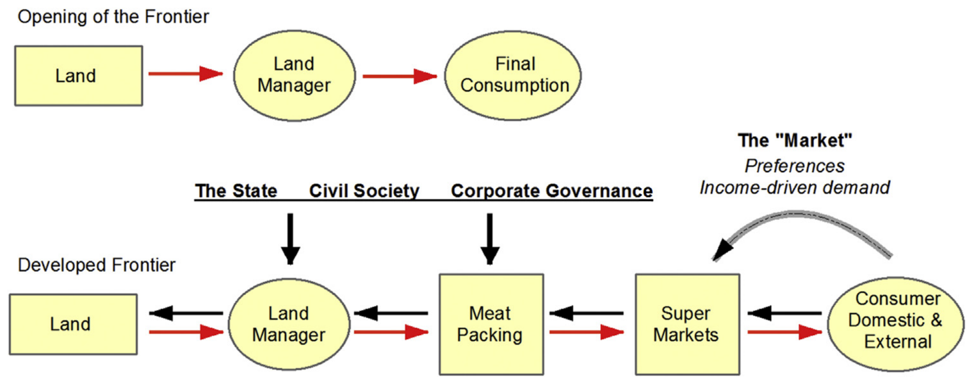

Fig. 2. Conceptual framework for the recent decline in deforestation rates.

plan was the addition of 20 million ha of conservation units and 10 million ha to expand the protected areas system (Abdala, 2008), which accounted for 37% of the region's total reduction in deforestation between 2005 and 2007 (Soares-Filho et al., 2010). In 2008, however, deforestation jumped 12% from the previous year and the government instituted PPCDAm-II (2008–2011), which is the analytical focus of our article. Among PPCDAm-II's several initiatives (Brasil, 2009), it is worth highlighting the embargo of private properties with illegal deforestation and intensification of field inspections by IBAMA, especially in municipalities with very high deforestation rates (see below). For example, in two highly publicized operations undertaken in 2008, IBAMA confiscated 20,000 m^3 of illegally harvested logs and 3000 head of cattle being raised in protected areas. Complementing IBAMA's actions, the Federal Prosecutors' Office (MinistérioPúblico Federal – MPF) of the State of Pará (MPF-Pará) initiated civil actions against 20 ranchers in noncompliance with environmental laws, and against 11 meat packing plants purchasing cattle from these farms (MPF-PA, 2009).

MPF-Pará also issued a recommendation to 69 supermarket chains, and other buyers of cattle products (such as leather), to avoid purchasing goods from the 11 plants involved in litigation (MPF-PA, 2009). These actions dovetailed with a Greenpeace campaign against the purchase of beef sourced from ranches disregarding labor and environmental laws. In the wake of these coordinated actions between State and civil society, 35 large Brazilian supermarket chains, and a number of buyers of other cattle products such as leather, discontinued purchases from the meat-packing plants in question. In addition, the Brazilian Supermarket Association announced new requirements for a certificate of origin from suppliers (Barreto and Araújo, 2012).

With a softer touch in 2009, MPF-Pará offered to suspend legal actions if the meat-packers in question agreed to buy cattle only from ranchers free from embargo and whose properties were registered with the State Environmental System – CAR, an online data base. Ranchers were also required to provide detailed plans to restore illegally deforested lands. As of 2013, over 72 thousand properties comprising 20 million ha were registered in CAR, nearly 80% of the total area under private ownership. Soon, MPF offices in other states began adopting this approach.[1]

[1] PPCDAm-II also included a measure by Brazil's Monetary Council (Resolução 3.545 of 29 February 2008) that demanded landowners to show legal title and proof that deforestation within property boundaries was legal, in order to obtain rural credit. The effectiveness of this measure may be little, given that the volume of credit in the Amazon increased from R$8.8 billion in 2007 to R$18.0 billion in 2011, and the number of credit contracts remained relatively constant (Banco Central do Brasil, 2014; tabulated by the authors).

Conceptual framework

The hypothetical reasons for the recent decline in deforestation rates are illustrated by Fig. 2, which depicts the beef commodity chain in an upper and lower panel. As the frontier opens, the production chain is simple (upper panel), with land managers (i.e. ranchers) providing meat to local populations, typically at municipal scale with deliveries to a slaughterhouse and retailing in a town market place. As regional development proceeds, production and distribution evolve in complexity. The commodities originate with the land manager as before, but now meat-packers intervene, butchering a variety of cuts and sending them, chilled, to supermarkets serving consumers both in Brazil and internationally. Deforestation is depicted on the far left of both upper and lower panels, where land functions as an input to cattle production. As the herd grows with increased consumption, more land is needed as an input to production, which implies deforestation in the absence of productivity gains.

A decline in deforestation has two possible sources, which are depicted in Fig. 2 as follows. Final consumption typically contracts with changing preferences, or because consumers, strapped for income, reduce their consumption of relatively costly items, such as beef. Declining consumption, which can arise due to economic hardship and recession, impacts the commodity chain all the way to its origin on the left, thereby reducing the land input, which is tantamount to a reduction in deforestation. Alternatively, policy interventions can impact the chain at various points, from left to right. State law with enforcement affects both land managers and meat-packers, who must reduce Amazonian land inputs to production or suffer consequences. As just discussed, alliances involving the state and civil society can achieve the same result, as was the case with MPF-Pará and Greenpeace. Finally, consumer preferences for beef sourced from non-Amazonian forest land can influence meso-scale entities such as corporations, which in turn exert pressure up the commodity chain to reduce inputs of Amazonian land, in effect inhibiting the penetration of the agricultural frontier into pristine forest (Jepson, 2006). A similar framework can be adapted to the soybean industrial complex.

Policy enforcement as a statistical treatment

The discussion to this point has indicated potential reasons for the decline in Amazonian deforestation occurring after 2008. An important consideration that leads to the statistical tests used in this article involves variation in the policy enforcement regime. In particular, if a sample of observations can be partitioned into two sub-samples differing with respect to an observable variation in policy enforcement, it is possible to implement panel analyses referred to broadly as "selection into treatment" methods. With this approach, one can measure how the specific treatment, in this case

Table 1
Pairwise Pearson correlation between deforestation and agricultural GDP, price of soybean and price of cattle in Brazil, in different periods.

	Deforestation (1988–2011)	$\text{Deforestation}_{t+1}$ (1988–2011)	$\text{Deforestation}_{t+1}$ (1988–1994)	$\text{Deforestation}_{t+1}$ (1995–2007)	$\text{Deforestation}_{t+1}$ (2008–2011)
Ag GDP_t	−0.141 (0.5112)	0.014 (0.950)	0.349 (0.443)	0.488 (0.091)	−0.983 (0.119)
Price of Soy_t	0.209 (0.327)	0.161 (0.463)	−0.038 (0.935)	0.721 (0.006)	0.849 (0.354)
Price of Cattle_t	−0.055 (0.798)	0.020 (0.926)	−0.367 (0.419)	0.720 (0.006)	0.156 (0.900)

Sources: Deforestation: INPE, Agricultural GDP: IBGE, Prices of Soy and Cattle: IEA/CATI – SAAESP.
Notes: Significance levels in parentheses below correlation coefficient. Monetary values used are in 1994 Brazilian Reais.

a battery of enforcement policies, impacted a variable of interest, namely the rate of deforestation.

As it turns out, policy enforcement varied across Amazonian counties, or municipalities, for the 2009–2011 period in question. Specifically, as part of PPCDAm-II implementation, the Federal Ministry of the Environment (MMA) placed 43 municipalities on a list for special enforcement efforts due to historically high deforestation rates. IBAMA increased the number of embargoed properties in targeted municipalities by 53% between 2007 and 2008, compared to an 11% increase in non-targeted municipalities (Barreto and Silva, 2010). The refusal of meatpacking plants to purchase cattle from the embargoed properties added weight to the policy regime. Similarly, the number of environmental fines issued in 2008 increased by 13% in the municipalities on the list compared to the previous year but declined 10% in the other municipalities.[2] In the discussion that follows, what we refer to as "municipalities on the list", or MOL municipalities, represent the "treatment" counties, in the language of panel analysis. They are thereby differentiated from municipalities "not on the list (MNL)," which constitute our 'control group' (n = 707; Fig. A1, Appendix).

To summarize, our unit of observation is the municipality, and our universe comprises both MOL and MNL municipalities. Our policy impact variable is the amount of deforestation occurring for the 2009–2011 period, as measured by INPE. In the three year period (2006–2008) prior to the implementation of policies, the 43 MOL municipalities accounted for almost half of the total deforestation of 38,764 km^2 in the Brazilian Amazon, out of 750 municipalities (Table 1). MOL municipalities deforested on average ~435 km^2 in those three years compared to only ~28 km^2 for MNL municipalities. For 2009–2011, deforestation dropped in both groups, but was more pronounced in the MOL group (60% reduction) than the MNL group (47%) (Table 1).

Methods

Our statistical methods are based on regression models capable of isolating so-called treatment effects, taken here to be the higher levels of enforcement of the policies described in the preceding section. To conceptualize the effect for the present application, let y_{i1} denote the deforestation rate for municipality i with higher enforcement, and y_{i0}, the rate without it. Note that in the empirical sample, we do not observe y_{i0} for MOL municipalities, or y_{i1} for MNL municipalities; the methods implemented are designed specifically for such cases. We define the efficacy of this heightened enforcement, or the "treatment," as the difference in deforestation rates $y_1 - y_0$. Of interest to the present paper is the average, or expected value, of this difference for the 43 MOL municipalities, or the *Average Treatment Effect on the Treated* (ATET). Formally, our methods yield:

$$\text{ATET} = E(y_1 - y_0 | w = 1),$$

where E is the expectation operator. For our case, placement on the list (w = 1) is not independent of deforestation, given the MMA created the MOL on the basis of (1) total deforested area since 1988, (2) total deforestation over the last three years, and (3) high rates of deforestation in at least three of the last five years, consecutively or not. This circumstance, together with our inability to observe both treatment states (w = 1 and w = 0) for individual municipalities, requires a different approach than standard regression based on ordinary least squares (OLS). Thus, we use two approaches designed for such situations, and referred to as *matching* estimators and the *difference in differences* model.

Matching methods

Matching estimators impute "missing outcomes" for y_{i1} by matching municipalities in the dataset that are similar to i but not MOL (n = 43). Similarity is established by distance measures applied to the so-called propensity score, $p(\mathbf{x})$, defined as the probability of treatment (higher levels of enforcement) given a set of covariates $\mathbf{x}$.[3] The MOL and MNL municipalities eligible for matching are given by those whose estimated propensity score, $\hat{p}$, lies within the range $[\max(\min(\hat{p}_1), \min(\hat{p}_0)), \min(\max(\hat{p}_1), \max(\hat{p}_0))]$, where $\hat{p}_1$, $\hat{p}_0$ are vectors containing estimated scores for the MOL and MNL municipalities, respectively. Each eligible MOL municipality is then matched to one or two MNL municipality on the basis of similar $\hat{p}$ scores, and the difference of the group means is interpreted as the treatment effect, ATET.[4] Matching methods require assumptions outlined in Appendix (A1.3) to consistently estimate the average effect.

Difference-in-differences

The difference-in-differences method calculates the impact of higher levels of policy enforcement by assessing the average differences in deforestation rates between two time periods (before-after) for each group of treated and untreated municipalities, or $(\bar{y}_{w=1,t=1} - \bar{y}_{w=1,t=0}) - (\bar{y}_{w=0,t=1}) - (\bar{y}_{w=0,t=0})$, where $\bar{y}$ is the average. This involves a pooled dataset for time periods (two periods of three years each, in our case) both before and after policy implementation in 2008 ($T_0 \equiv$ 2006–2008 and $T_1 \equiv$ 2009–2011). Here, subscript t = 1 or 0 indicates time, with

[2] These numbers refer to environmental fines in the categories 'flora' and 'ecosystem,' which encompass illegal deforestation and logging. Excluded are fines related to fauna, urban, and industrial violations. Tabulation conducted by the authors with data provided by IBAMA.

[3] In the present application, $p(\mathbf{x})$ was estimated using a probit model, using past deforestation rates (pre-2008) in the $\mathbf{x}$ vector, the criteria used by MMA for inclusion on the list.

[4] The standard errors of ATET are corrected for the two-step process (Abadie and Imbens, 2011). Studies have shown that matching using propensity score is highly sensitive to the set of variables included in the first stage score estimation (Smith and Todd, 2005). Moreover, when data exhibit strong selection, simulations suggest that more than one treated unit per stratum should be allowed, instead of a single nearest neighbor (Augurzky and Kluve, 2007). For such reasons, we estimate propensity scores with different first stage specifications and different sets of nearest neighbors.

$y_{j0} = D2006_j + D22007_j + D2008j$, where D is deforestation in municipality j for the year as indicated. Similarly, y_{j1} is the sum of annual deforestation from 2009 to 2011. Let w_j indicate treatment status for municipality j with $w_j = 1$ for MOL and $w_j = 0$ otherwise; let P indicate period, with $P_{j0} = 0$, and $P_{j1} = 1$. The policy effect is obtained by estimating α in the following model (Wooldridge, 2002):

$$y_{jt} = \theta + \delta P_{jt} + \beta w_j + \alpha P_{jt} \times w_j + \mu$$

where the interaction term $P_{jt} \times w_j = 1$ indicates MOL in the post-policy period.[5]

Avoided deforestation and carbon emissions

The paper uses its statistical findings to calculate the amount of avoided carbon emissions stemming from policy enforcement, and also to assess ecoregion-specific savings in land area. For the avoided emissions analysis, we use biomass data from Baccini et al. (2012) who produced a 500 m cell resolution raster of above ground biomass, which we converted to carbon emissions by using the 2:1 ratio commonly found in the literature (Baccini et al., 2012, Saatchi et al., 2011). The total amount of avoided emissions, C, is calculated as $C = (\sum_{i \in MOL}^{n} c_i/n) \times \text{ATET} \times 43$, where c_i is the carbon content for each 1 km^2 forested cell in MOL municipalities, n is the total number of forested cells in MOL municipalities, and ATET is the average avoided deforestation in km^2. Our carbon estimates are conservative since we did not include below ground biomass values.

For ecosystem impacts, we calculate the ecoregion-specific areas spared from deforestation. We do this by first using the SimAmazonia land change model (Soares-Filho et al., 2010, 2006) to predict deforestation in the absence of policy enforcement, and to rank forest pixels on the basis of deforestation likelihood. We then return avoided deforestation to the 43 MOL counties on the basis of the deforestation likelihoods, using the most optimistic statistical estimate (difference-in-differences; see Results). We generate maps for both cases, and overlay them to identify pixels that would have been deforested in the absence of policy enforcement in the MOL. We intersect this result with a terrestrial ecoregion map (Olson et al., 2001) to determine the areas spared from deforestation on an ecosystem basis.

Results

Statistical findings on difference in enforcement levels

All statistical methods estimate a policy impact on deforestation rates in the MOL group, although the magnitude and significance levels vary. The *difference in differences* method yields a point estimate and the largest effect, a ∼247 km^2 reduction in the post-policy 3 y period (2009–2011) or 82 km^2 y^{-1} per municipality (Table 2).[6] *Matching with propensity score* methods estimate smaller average effects, with reductions ranging between 53.59 and 75.70 km^2, although the lower bound is only marginally significant at 6%. All results show a negative sign for the impact of policy on deforestation in MOL municipalities, which is in stark contrast with the simple OLS regression result without any correction for selection into treatment (raw difference of approximately +160 km^2). The propensity score 1 (PS1) model uses all past deforestation data prior to 2008 to calculate the propensity score and then compares single-matches between treated and untreated municipalities. PS2 uses only past deforestation data that was statistically significant in the score calculation and single matches (1 MOL and 1 MNL municipalities). Finally, PS3 uses only statistically significant past deforestation data, but with two nearest neighbors as matches. In all propensity score models, the first stage probits were highly significant in explaining treatment, with pseudo-R^2 around 0.80 (see Appendix for full results) (Table 3).

Table 2
Estimated impact of policies, difference in differences method.

Variables	Coef.	Total avoided emissions (Pg C)
P	−13.18** (2.30)	
w	407.52** (64.91)	
wxP	−247.75** (72.78)	1.44×10^{-1}
Constant	28.32** (1.94)	

Notes: $N = 1500$, $R^2 = 0.394$, robust standard errors in parentheses below coefficients.
** Significant at 0.01 level.

Carbon and ecosystem implications

The average treatment effect (on the treated – ATET) can be translated to basin scale by multiplying the estimated values by the number of MOL municipalities (i.e. ATET × 43); this shows avoided deforestation to range between 2304 and 10,653 km^2. Translating reduced magnitudes of deforestation into carbon savings (Baccini et al., 2012) shows that for the period 2009–2011, intensified policy enforcement efforts in question managed to avoid between 3.13×10^{-2} and 1.44×10^{-1} Pg of C. The upper range corresponds to about 14% of annual global emissions from land use change in the tropics (Baccini et al., 2012). As for ecosystem impacts, the statistical results indicate a spatially heterogeneous outcome, with more tropical moist forest being conserved (62%) than seasonal, dry forest (27.5%). In general, the conservation occurs in the southern and eastern parts of the basin, in the area referred to as the arc of deforestation. The dry forests conserved are found entirely in Mato Grosso, which perhaps reflects that state's efforts to reduce losses of its primary forests. The tropical moist forests left intact (white dots in Fig. 3) are found in the Rondônia (The Madeira/Tapajós Forest), Tapajós (The Tapajós/Xingu Forest), and Xingu (Xingu/Tocantins-Araguaia) areas of endemism, and stretch into Maranhão (The Tocantins-Araguaia/Maranhão Forest) (Silva et al., 2005).

Discussion

The analysis provides strong evidence for the existence of a policy enforcement effect for PPCDAm-II in Amazonia's MOL municipalities. Nevertheless, spurious results cannot be ruled out a priori. For example, MOL municipalities reside more closely to state capitals and benefit from better transportation infrastructure, which could make them more observable to enforcement, and therefore policy-responsive. For these same reasons, MOL municipalities are generally economically vibrant, with strong links to the global economy (Macedo et al., 2012; VanWey et al., 2013) that would make them potentially vulnerable to economic downturns such as the Great Recession of 2008.

We believe such alternative explanations do not explain the ATET effect as measured, and that it is attributable to policy enforcement differentials. Past deforestation data, included in the determination of propensity scores, provide a powerful control for differences in enforcement effort across the two groups, because past deforestation correlates strongly with road quality and proximity to urban centers (Andersen et al., 2002; Chomitz

[5] Although the method requires that unobservables in μ not be correlated with the policy change variable, it controls for any temporally invariant bias present in the data (Smith and Todd, 2005).

[6] The parameter δ is the change in deforestation in all municipalities from the pre to post-policy period (−13 km^2) and the parameter β captures deforestation in the MOL municipality not attributable to policy (408 km^2). The intercept (28 km^2) is the average pre-policy deforestation in the MNL municipalities.

Table 3
Estimated impact of policies, matching methods.

Matching method	Estimated average effect (2009–2011), km^2	Total avoided emissions (Pg C)
Propensity score 1	−53.59* (32.94)	3.13×10^{-2}
Propensity score 2	−75.70** (38.53)	4.43×10^{-2}
Propensity score 3	−74.73** (28.70)	4.37×10^{-2}

Notes: $N = 750$, standard errors in parentheses below coefficients, corrected for two step procedure. Estimates are average treatment effect on the treated (ATET). See Appendix for details of first stage probit.
* Significant at 0.06.
** Significant at 0.01 level.

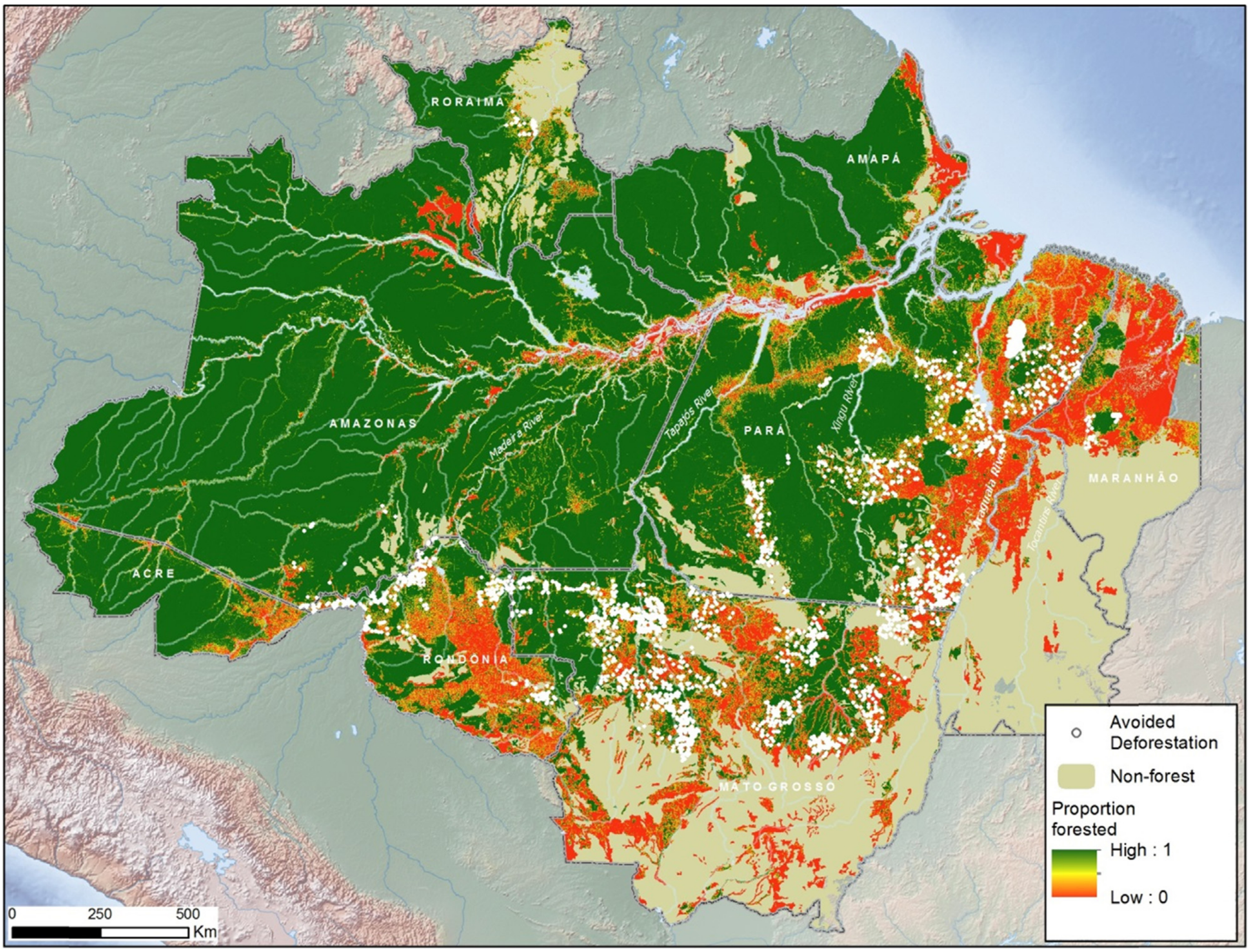

Fig. 3. Avoided deforested area for the 2009–2011 period, in white (10,653 km^2).

and Gray, 1996; Pfaff et al., 2007). Thus, by using past deforestation in the score estimation, we indirectly control for differences in infrastructure quality. Although recent road investments or road deterioration after 2008 could have impacted levels of enforcement, we are unaware of any systematic biases in this regard. As for a differential effect associated with the Great Recession of 2008, the global downturn had little impact on Amazonia's agricultural sector (Fig. 4A). In fact, after 2008, both MOL and MNL municipalities expanded their planted areas in soybeans, whose prices are set in international markets. The same conclusion holds for all annual crops (not shown but available upon request). A similar situation prevails for the cattle herd (Fig. 4B), with growth more pronounced in MOL than MNL municipalities during the post-policy period.[7] Thus, there is no sign that the MOL group was disproportionately hit by the economic downturn.

In fact, our analysis probably underestimates the overall impact of policies and enforcement for two reasons. First, our research design focuses on a specific set of policies enforced over a relatively short period (PPCDAm-II), in which case our treatment effect indicates reduced deforestation against a background of ongoing reduction, attributable to other long-standing policies (e.g. adherence to the forestry code). Consequently, our results may be interpreted as providing a lower bound to the impact of policy, overall. The second reason for suspecting underestimation is that the analysis implemented does not capture spillover effects spreading from MOL to neighboring municipalities. For instance, farmers

[7] The drop in production observed in 2006 in all graphs is likely to be due to a correction in (over) estimates of previous years. This municipality level production dataset is based on estimates and is corrected once the Agricultural Census is released, which occurred in 2006.

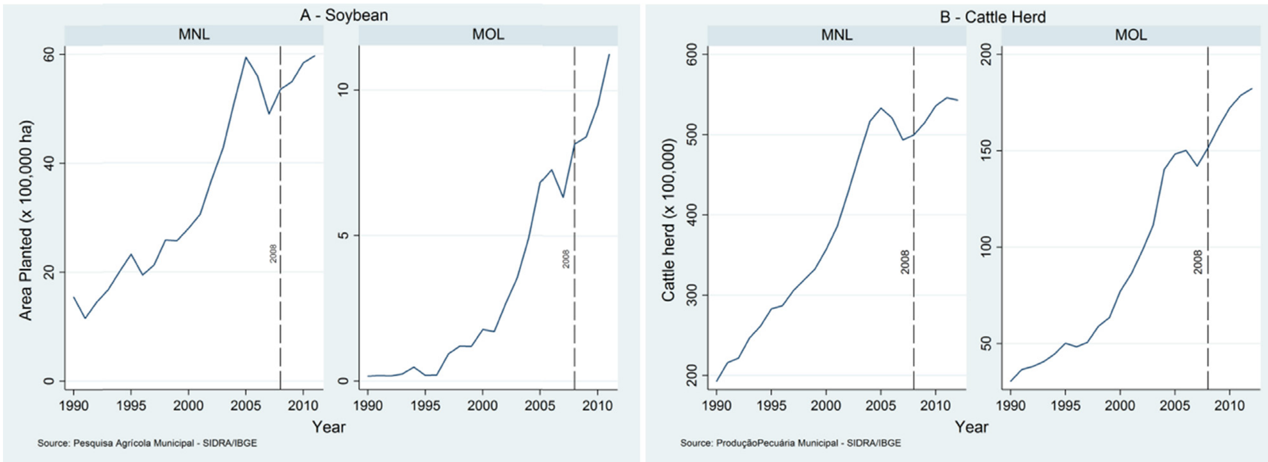

Fig. 4. (A) Area planted in soybeans from 1990 to 2011 in MNL and MOL and (B) cattle herd evolution from 1990 to 2011.

in MNL areas might have been persuaded to deforest more judiciously upon perceiving associated risks after 2008. Such potential bias would be difficult to correct given the lack of heterogeneity across municipalities and through time.

Industry-led initiatives such as the 'soy moratorium' have apparently helped reduce deforestation, particularly in Mato Grosso State (Macedo et al., 2012; VanWey et al., 2013). Our analysis cannot separate the efficacy of these meso-scale initiatives (Jepson, 2006) from the policy enforcement regime if participating farms are all located in the MOL treatment group. In this case, the soy moratorium effect is absorbed into the overall treatment effect as measured. On the other hand, if participating farms are distributed in both MOL and MNL, then the measured treatment effect is indeed attributable strictly to differences in policy enforcement efforts.

That the decline in deforestation after 2008 is likely due in large part to policy, not economic downturn, invites speculation about the social and institutional circumstances that led the State and Civil Society to demand, enact, and enforce more stringent environmental policies (Fig. 2). Although democratization put the necessary institutional tools in place with the creation of an independent judiciary and a free press, deforestation through the 1990s showed little restraint. Indeed, for many years Brazilian land owners paid little regard to environmental laws and regulations (McAllister, 2008), and the Amazon region was no exception. Here, ranchers and farmers were required by the forestry code to keep at least 50% of their property in a forest reserve starting in 1965, but the Brazilian space agency (the Space Research National Institute, or INPE), which began monitoring deforestation in 1988, soon showed that the forestry code had little traction.

We suggest that an accumulation of information, including the precise yearly measurements of deforestation provided by new geospatial technologies, ultimately made the difference. As the public learned that 75% of Brazil's CO_2 emissions were coming from changes in land cover and that large increases in agricultural output could feasibly be achieved by making better use of the 70 million ha that had already been deforested (Brasil, 2004; EMBRAPA and UNICAMP, 2008), they grew increasingly supportive of conservation efforts. This dovetailed effectively with reform in the Brazil judiciary in the 1988 constitution, which transformed the MPF into an independent branch of government responsible for defending 'collective and diffuse' rights. Today, the MPF has evolved into one of Brazil's most important institutions for the enforcement of environmental law (McAllister, 2008). Its independence even allows it to prosecute governmental agencies in addition to private interests, making it a watchdog institution capable of "enforcing enforcement." In 2012 for example, the MPF brought legal actions against IBAMA in Rondônia State, alleging widespread corruption. The new institutional role of the MPF represents an upscaling of frontier governance to national interests, including those of Brazilian citizens living in urban environments. Finally, the MPF success relied on a well-crafted legal framework, such as the Environmental Crimes Law of 1991 and the various incarnations of the Forestry Code of 1965, both of which were fundamental in defining what illegal deforestation entailed.

Conclusion

Despite the recent successes noted, Brazil needs to bring its annual deforestation rate down from 5000 to 3800 km^2, in accordance with its National Climate Change Plan (NCCP) which calls for an 80% reduction by 2020, from the baseline average rate observed for the period, 1996–2005. Notable challenges remain, as global demand for Amazonian agricultural commodities continues to grow (Walker et al., 2009; Garrett et al., 2012), and as investments in hydropower and road paving continue to be made. These factors could easily lead to new rounds of in-migration and associated deforestation (Nazareno and Lovejoy, 2011). Also of concern are efforts to reduce the extent of existing protected areas, to weaken environmental law (e.g. the forestry code), and to provide amnesty for illegal deforestation prior to 2008. In fact, monitoring systems have captured a 28% increase in deforestation in 2013 when compared to the previous year (INPE, 2014). Potential leakages to other ecosystems within Brazil, particularly the Cerrado, and to other parts of the world such as the Argentinean and Paraguayan Chaco, may also offset the environmental benefits from declining deforestation in the Amazon (Clark et al., 2010; Caldas et al., 2013; Lapola et al., 2014). Although the field of caveats is wide, and the road to meeting its NCCP objectives is long, Brazil has taken actions which, if continued, raise hopes about the future of Amazonia, and about the possibilities of success for REDD programs worldwide.

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Appendix A.

A.1. Statistical analyses

A.1.1. OLS regression results without selection into treatment correction

A simple OLS regression without any correction for selection into treatment shows a spurious positive effect of the policies (i.e. inclusion on the list) on deforestation, even when controlling for typical covariates such as protected areas within the municipality, rainfall, mean distance to an official road, and mean distance to previous deforested areas (results available upon request).

Variables	Coef.	Std. err.	t	$P>\|t\|$	[95% Conf. interval]	
MOL	159.766	9.519	16.78	0.000	141.08	178.45
Constant	15.139	2.279	6.64	0.000	10.66	19.61

$N = 750$ and $R^2 = 0.273$.

A.1.2. Matching methods

(a) Propensity score 1: single nearest neighbor with overlapping observations only; first stage probit model using all past deforestation data.

First stage probit
Number of obs = 750
Pseudo $R^2 = 0.81$
Log likelihood = −31.065

Variables	Coef.	Std. err.	z	$P>\|z\|$	[95% Conf. interval]	
d_to97	0.0003	0.0002	1.430	0.152	−0.0001	0.0007
d97_2000	0.0016	0.0019	0.850	0.397	−0.0021	0.0054
d_2001	−0.0024	0.0030	−0.790	0.431	−0.0083	0.0036
d_2002	0.0014	0.0027	0.510	0.611	−0.0039	0.0067
d_2003	0.0014	0.0012	1.180	0.240	−0.0009	0.0038
d_2004	0.0001	0.0032	0.030	0.973	−0.0062	0.0064
d_2005	0.0171	0.0052	3.280	0.001	0.0069	0.0273
d_2006	0.0067	0.0064	1.040	0.297	−0.0059	0.0193
d_2007	−0.0054	0.0087	−0.620	0.538	−0.0225	0.0117
d_2008	0.0125	0.0044	2.820	0.005	0.0038	0.0212
Constant	−4.8249	0.7951	−6.070	0.000	−6.3832	−3.2665

First stage estimation using all past deforestation data explains very well the treatment (i.e. why certain municipalities were included on the list) as indicated by the high pseudo-R^2 (0.81) but several previous deforestation variables were not significant, particularly those between 1997 and 2004. The inherent trade-off when selection is strong is that there are less overlapping observations, which reduced the number of observations to 118 municipalities.

(b) Propensity score 2 and 3: first stage probit using only deforestation data that showed significant effect in (a).

First stage probit
Number of obs = 750
Pseudo $R^2 = 0.7971$
Log likelihood = −33.417

Variables	Coef.	Std. err.	z	$P>\|z\|$	[95% Conf. interval]	
d_to97	0.0004	0.0002	2.300	0.021	0.0001	0.0007
d_2005	0.0183	0.0033	5.460	0.000	0.0117	0.0248
d_2006	0.0131	0.0041	3.210	0.001	0.0051	0.0211
Constant	−4.3098	0.5997	−7.190	0.000	−5.4852	−3.1345

The first stage probit using only the past deforestation variables that were significant in the previous regression (i.e. deforestation prior to 1997, deforestation in 2005 and 2006) can still strongly explain selection into MOL; the pseudo-R^2 is still around 0.80.

A.1.3. Assumptions for matching estimators

(a) Ignorability of treatment

When w and (y_0,y_1) are correlated, an assumption is needed to identify the treatment effect. Let $\boldsymbol{x}$ denote a vector of observed covariates. The assumption is that w and (y_0,y_1) are independent, conditional on x. This also implies $E(y_0|w,x) = E(y_0|x)$ and $E(y_1|w,x) = E(y_1|x)$. The assumption holds if w is a deterministic function of $\boldsymbol{x}$, also condition known as "selection on observables." In the present case, this assumption is plausible because municipalities were added to the list on the basis of (1) total deforested area since 1988, (2) total deforestation over the last three years, and (3) high rates of deforestation in at least three of the last five years, consecutively or not.

(b) Overlap

For all $x \in X$, where X is the support of the covariates, we assume that $0 < P(w = 1|x) < 1$ .If the condition fails, then we cannot observe control and treatment units with the same values of covariates, in which case there will be no matching of treated and untreated municipalities.

A.1.4. Municipalities included on the list

The first list of MMA MOL municipalities included Alta Floresta, Altamira, Aripuanã, Brasil Novo, Brasnorte, Colniza, Confresa,

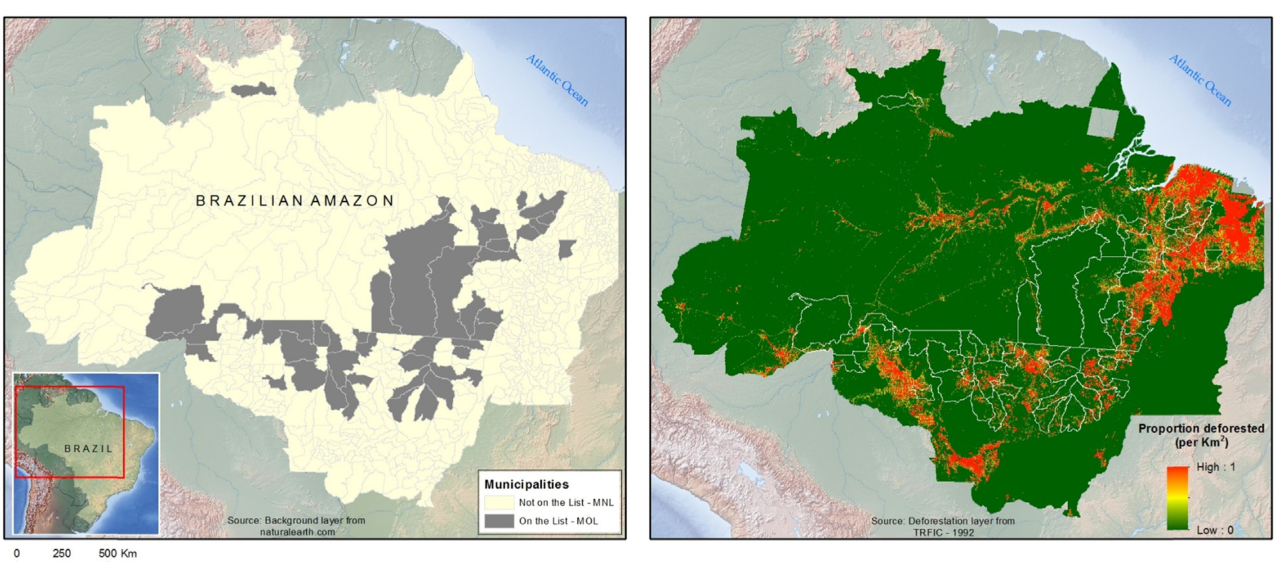

Fig. A1. Municipalities on the list (MOL) – left; and proportion deforested in each 1 km^2 cell as of 2008 – right.

Cotriguaçu, Cumaru do Norte, Dom Eliseu, Gaúcha do Norte, Juara, Juína, Lábrea, Machadinho d'Oeste, Marcelândia, Nova Bandeirantes, Nova Mamoré, Nova Maringá, Nova Ubiratã, Novo Progresso, Novo Repartimento, Paragominas, Paranaita, Peixoto de Azevedo, Pimenta Bueno, Porto Velho, Querência, Porto dos Gaúchos, Rondon do Pará, Santa Maria das Barreiras, Santana do Araguaia, São Félix do Araguaia, São Félix do Xingu, Ulianópolis, and Vila Rica. This list of 36 was quickly expanded to 43 with addition of Amarante do Maranhão, Feliz Natal, Itupiranga, Marabá, Mucajaí, Pacajá, and Tailândia. In 2011, seven more municipalities were added (Alta Boa Vista, Boca do Acre, Cláudia, Grajaú, Moju, Santa Carmen, and Tapurah) and two removed (Paragominas and Querência). We used the original 43 municipalities in our statistical analyses. In order to be removed from the list, a municipality must (1) have 80% of its area in private ownership registered in the CAR system, (2) realize a deforestation rate less than 40 km^2 in the preceding year ($t-1$), and (3) show an average deforestation rate for years $t-2$ and $t-3$ that is at least 60% below the average from $t-4$, $t-5$, and $t-6$.

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