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Fire regimes in Amazonia: The relative roles of policy and precipitation

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ABSTRACT

Reducing carbon emissions from deforestation and forest degradation is now a vital component in climate change mitigation strategies. Global initiatives such as REDD+ are receiving growing investments, and in-country policy makers are under pressure to protect intact forests. In 2008, Brazil met these pressures by making deforestation reduction a central piece of its climate change policy. Although previous research found that this policy led to reduced deforestation, decreases in fire–another significant factor in carbon emissions–were not observed. Here we revisit Amazonia, the target location of Brazil's anti-deforestation policies, to determine how precipitation may be affecting forest fires in the area while controlling for other potential biophysical, economic, and institutional correlates. Using data on precipitation and deforestation alongside MODIS active fire and burned area data, this article examines the general spatial-temporal trends of fire in the region between 2001 and 2013. We then implements statistical models to measure the relative impact of precipitation and anti-deforestation policies on both fire events and burned area over the time period. The analysis shows that while deforestation decreased under policy treatment, forest fires were less responsive to policies. Furthermore, the analysis provides strong evidence for the existence of a precipitation effect on both fire events and burned area. Results indicate that a one standard deviation decrease in precipitation from its normal could increase fire events by 11–15% and burned area by 18–27%. The article concludes by addressing the challenges in controlling fire in Amazonia under drier climatic conditions in the presence of abundant fuel and ignition sources.

1. Introduction

The mastery of fire was a turning point in our species' biological and technological evolution and is intricately linked to the onset of the Anthropocene (Steffen et al., 2007; Glikson, 2013). Natural and anthropogenic fires have long played a pivotal role in terrestrial and atmospheric system processes (Bowman et al., 2009) but encroachment of modern agriculture into tropical forests has increased the quantity and frequency of fire in these ecosystems (Neves et al., 2004; Bush et al., 2008). Now, with global initiatives set to reduce carbon emissions from land change (Kollmuss et al., 2008), policymakers are under increased pressure to not only curb deforestation and forest degradation, but also combat fire.

Brazil is notable in this regard because its Amazonian forests hold close to 35% of the world's tropical forest carbon and produces some of the largest emissions from forest loss (Saatchi et al., 2011; Baccini et al., 2012). The Brazilian Amazon has also been hailed as a success story in the reduction of deforestation rates in the last decade, attributed in large part to the successful implementation of public policies (Soares-Filho et al., 2010; Arima et al., 2014; Cisneros et al., 2015). Given the strong relationship between deforestation and anthropogenic fires, the same steep reductions in fire were expected. Instead, fire numbers fluctuated greatly from year to year, possibly influenced by intervening abiotic factors.

The objective of this article is to tackle this issue and examine the main factors that drive the current fire regime in Brazil's Amazonia. Specifically, we examine the relative roles of abiotic factors and anti-deforestation policies in determining the amount of forest fires, while controlling for other potential biophysical, economic, and institutional correlates.[1] To pursue this objective, we first discuss the relationship between deforestation, agricultural expansion, and fire in the basin, while acknowledging the role

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[1] Research has found that indigenous reserves and conservation areas experience much lower levels of fire than their non-protected counterparts, even when controlling for the fact that those protected areas are typically located in remote areas far from agricultural activities (Arima et al., 2007; Nelson and Chomitz, 2011; Barber et al., 2014).

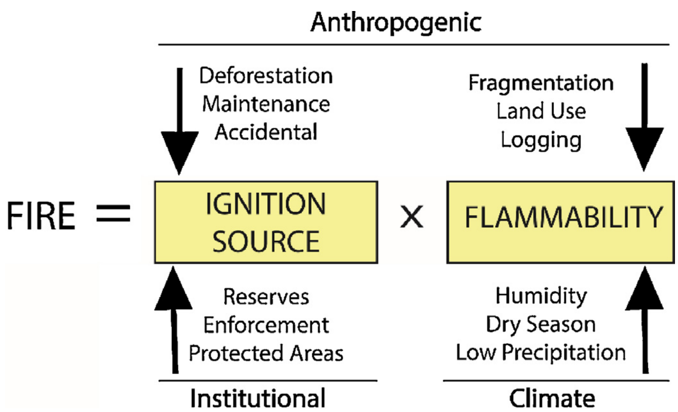

Fig. 1. Conceptual framework for the drivers of fire.

of climatic factors and policy initiatives to date. Next, we show evidence that fire and deforestation rates decoupled from each other after 2007, a main motivation for our analyses. We then present statistical analyses that reveal the extent to which two factors—(1) recent policy measures and (2) deviations in regional precipitation—have affected fire in the Amazon, both in terms of total number of fire events and burned area. Finally, we translate these results into practical significance for policymakers, whose engagement in mitigation strategies may be offset by the precipitation and climate trends of the future.

2. Background

2.1. Anthropogenic fires in Amazonia

Although natural wildfires are relatively rare in the Brazilian Amazon, anthropogenic fires remain a regular threat (Uhl et al., 1989; Uhl and Kauffman, 1990; Cochrane et al., 1999; Nepstad et al., 1999; Sorrensen, 2009; Aragão and Shimabukuro, 2010; Alencar et al., 2011; Brando et al., 2013; Shlisky et al., 2009). These fires are tightly linked to the encroachment of the agricultural and logging frontiers into primary forest. Numerous studies have found a strong statistical relationship between fire incidence and agricultural activity, typically proxied by distance to roads, farmgate prices, and distance to deforested areas (Nepstad et al., 2001; Alencar et al., 2004; Arima et al., 2007; Barber et al., 2014). In addition, logging and forest fragmentation increase fuel loadings (i.e litter material) and decrease understory humidity (Uhl and Kauffman, 1990; Cochrane and Schulze, 1999; Nepstad et al., 2001), while millions of farmers and ranchers provide the ignition sources as they use fire to burn forest biomass during the deforestation process. Burns are often followed by the encroachment of grass species, increasing fine fuel loads and fire intensity (Veldman et al., 2009; Silvério et al., 2013; Brando et al., 2014). Once planted pastures are established, ranchers often use fires to control invasive shrubs and trees (i.e. maintenance fires) that compete with the desired grasses (Uhl and Buschbacher, 1985; Nepstad et al., 1999, 2001; Laurance et al., 2001; Sorrensen, 2009; Arima et al., 2007; Schroeder et al., 2009; Walker et al., 2009). The end result is that even accidental fires in the Amazon are anthropogenic in origin; the result of deforestation or maintenance fires that escape control and advance into logged or primary forests (Holdsworth and Uhl, 1997; Nepstad et al., 1999, 2001).

2.2. The role of abiotic conditions

Ignition sources from human activities are necessary but wildfires can only ignite and spread if abiotic conditions are adequate to transform vegetation into flammable material. Climatic parameters, including precipitation, humidity, wind speed (Aragão et al., 2008; Marengo et al., 2008; Alencar et al., 2015), and events such as the El Niño Southern Oscillation (ENSO) or extreme droughts are all important factors (Nepstad et al., 1995; Barbosa and Fearnside, 2000; Nepstad et al., 2001; Galindo et al., 2003; Marlon et al., 2008; Alencar et al., 2011; Brando et al., 2013; Brando et al., 2014). For instance, recurrent fires occur more often during ENSO years (Alencar et al., 2004, 2011, 2015), and recent work has also shown a strong linkage between the Atlantic Multidecadal Southern Oscillation Index and patterns of precipitation and fire in the southern and southwestern Amazon (Chen et al., 2011). If burned more than once, these forests experience a dramatic increase in the risk of understory fire (Alencar et al., 2004; Morton et al., 2013) and up to a 28% increase in their chances of being burned a subsequent time (Alencar et al., 2011). Subsequent burns may lead to altered regeneration patterns (Balch et al., 2013), increased susceptibility and burn intensity (Cochrane and Schulze, 1998; Cochrane et al., 1999) and increases in global atmospheric CO_2 (a figure that reached 395.31 ± 0.10 ppm in 2013 according to the Quéré et al. (2015)). In some parts of the Brazilian Amazon, the return interval for fires is already 5–11 times more frequent than estimates for natural fire regimes (Alencar et al., 2011).

2.3. Environmental policies and the link between deforestation, fire & precipitation

In this section, we review the recent anti-deforestation policies implemented in Brazil and show how, despite an early correlation, fire and deforestation rates decouple from each other after 2007; perhaps because fire regimes respond not only to policies but also to abiotic conditions.

Following the 27,772 km^2 of deforestation observed in 2004, Brazil enacted the first Action Plan to Prevent and Control Deforestation in Amazonia (PPCDAm-I). Implemented between 2004 and 2007, this plan restructured Brazil's environmental agency's mission (IBAMA) to focus exclusively on enforcement and regulation. IBAMA began using INPE's 'real-time' deforestation detection (DETER) to target its enforcement efforts in the field (Abdala, 2008), and the country's protected areas were expanded dramatically. Between 2004 and 2008, 25 million hectares of federal conservation units, 10 million hectares of indigenous lands, and 25 million hectares of state conservation units were added to the protected areas system in Amazonia (Abdala, 2008). These efforts were followed by the second phase of PPCDAm (2008–2011), focused on monitoring and enforcement of environmental legislation. As part of this new phase, 36 municipalities were placed on a list for special enforcement efforts due to historically high deforestation rates. This list was later expanded to 43 (2009) and 48 municipalities (2011). As of 2012, 46 municipalities remain on the list (52 municipalities were blacklisted in total) (Fig. 2).

Once on the list, landholders in those municipalities were subjected to greater monitoring scrutiny (i.e. more fines and citations for non-compliance with environmental laws) (Barreto and Silva, 2010; Arima et al., 2014). To this day, removal from the list is contingent upon sustained reduction of deforestation rates, creation of georeferenced cadastral maps of private properties, and plans for restoring areas deforested illegally in each property (MMA, 2013). In addition, in 2009, federal prosecutors initiated civil actions against meat packing plants purchasing cattle from non-compliant farms. As part of the initiative, prosecutors offered to suspend the actions if companies agreed to purchase cattle only from ranches that followed the directives established by PPCDAm. Together, these actions have been hailed as a success story in

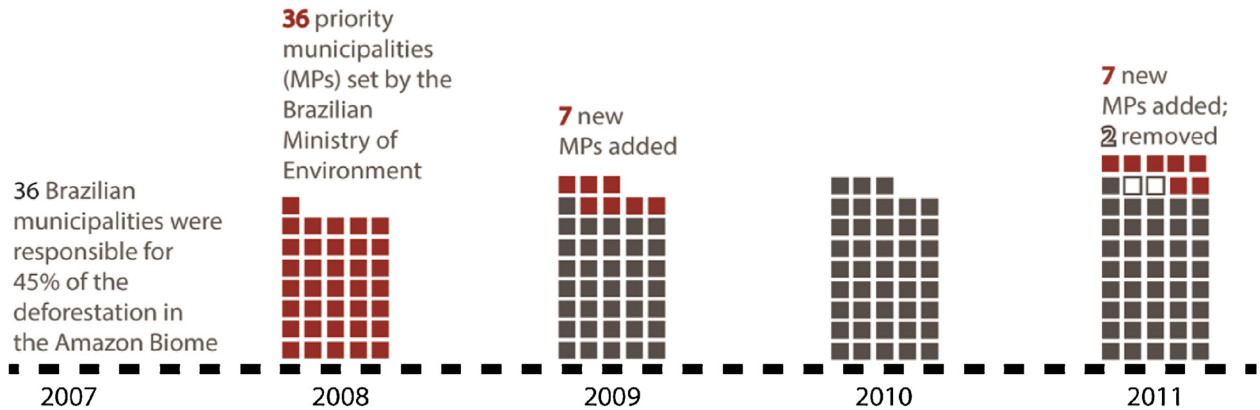

Fig. 2. PPCDAm-II originally placed 36 municipalities on a list for special enforcement efforts due to historically high deforestation rates. This list was later expanded to 43 (2009) and 48 municipalities (2011), after two municipalities were dropped from the list. Since 2012, 46 municipalities remain on the list (52 municipalities were blacklisted in total).

reducing deforestation to historically low levels (Soares-Filho et al., 2010; Arima et al., 2014; Assunção et al., 2012).

While deforestation declined under these policies, fire did not follow the same downward pattern. In 2010, a study by Aragão and Shimabukuro found that fire occurrence increased in 59% of the area where deforestation had been reduced. A closer examination of deforestation data from INPE alongside MODIS fire events[2] and burned area[3] reveals that this trend began even earlier. While deforestation rates correlate positively with fire events (r = 0.532) and burned area (r = 0.430) from 2001 and 2006, this positive correlation breaks in 2007. At this point, fire events increase by 70% (from 236,684 to 406,408) and burned area quadruples with respect to the previous year (from 19,811 to 90,100 km^2), despite a continuing decline in deforestation. This decoupling between fire and deforestation persists in the 2008–2013 period when the correlation between burned area and deforestation becomes negative (r = −0.156) and almost zero with respect to fire events (r = 0.008). Interestingly, the most prominent years of fire increase—2007 and 2010—were also years of below-normal precipitation,[4] suggesting abiotic conditions may have a role to play (Fig. 3).

These changes in correlations between fire and deforestation, as well as the inconsistent impact of anti-deforestation policies, lends support to two hypothetical lines of reasoning behind the observed fire regime. On one hand, decrease in fires could be due to anti-deforestation policies; on the other, increase in fires may be due to below normal precipitation in certain years. The goal of this article is to determine the effect of those two confounding factors on forest fires in Amazonia between the years 2001 and 2013.

3. Analytical framework & data processing

A main analytical challenge of this study is to control for the effect of non-random blacklisting of municipalities. The Brazilian government used historical deforestation information (INPE-PRODES) to decide which municipalities should be blacklisted under the policy (Arima et al., 2014). Since wildfires are linked to deforestation, any attempt to calculate the effect of this policy on fire without controlling for selection into treatment (i.e. blacklisting) is likely to be biased. One alternative would be to use matching estimators to identify the counterfactual scenario of what would have happened with fire in the absence of policies. However, although matching methods with panel data exist, they usually involve shrinking the time dimension into two periods, pre- and post-policy. This strategy could identify the *average* effect of blacklisting (i.e. average treatment effect) on fire, but it would not identify the *marginal* impact of rainfall variation on fire throughout the period or assess the longer term impact of blacklisting in subsequent years. One alternative is to implement panel econometric models due to their ability to identify the static and dynamic effects of blacklisting as well as the effect of rainfall variation, provided that selection into treatment is controlled for (Wooldridge, 2010). Given the strengths of both matching and panel estimators, we adopt a two-pronged approach whereby matching estimators are used as a pre-processing step to select sample units that are comparable with respect to certain pre-blacklisting characteristics. Panel models are then applied on that matched dataset to estimate the effect of the variables of interest. By removing sample units in one group (not listed or listed) without a comparable unit in the other group (listed or not listed) we reduce bias in the subsequent regressions.[5] This approach has been shown to make parametric models (e.g. panel regressions) less-model dependent and more accurate in causal inference (Hsiao, 2007).

The matching procedure was implemented as follows. First, we created a cross-sectional dataset of all municipalities in Amazonia (n = 772) and a treatment binary variable if the municipality was ever blacklisted in any given year. We then calculated the propensity score of being listed or not through a logit regression with explanatory variables that included historical deforestation prior to 2001, which was the main criteria for blacklisting (see Table A1 in Appendix A). One municipality was matched to one or more municipalities from the other treatment group if their propensity scores were within a caliper distance of 0.093. This value is the product of the standard deviation of the propensity scores (s.d. = 0.169) by 0.55. The scalar 0.55 is the upper bound of the range of values that minimized the bias in a Monte Carlo simulation study when at least one of the covariates used in the propensity score was continuous (Austin, 2011). Forty-eight municipalities were discarded, of which 15 were from the blacklisted group and the remaining were from the non-listed

[2] Fire events are defined as the annual count of fire occurrences according to MODIS Collection 5 Active Fire Data, Fire Information for Resource Management System (FIRMS) product MCD14ML.

[3] Burned Area is defined as the number of 0.25-km^2 pixels according to MODIS Collection 5.1 Burned Area Data product MCD45A1, which uses Terra and Aqua satellites to identify what areas have burned on a monthly basis.

[4] TRMM average annual precipitation in mm*$pixel^{-1}$ per year according to Tropical Rainfall Measuring Mission (TRMM) product 3B43.

[5] This is known as the overlap condition in propensity matching estimators literature.

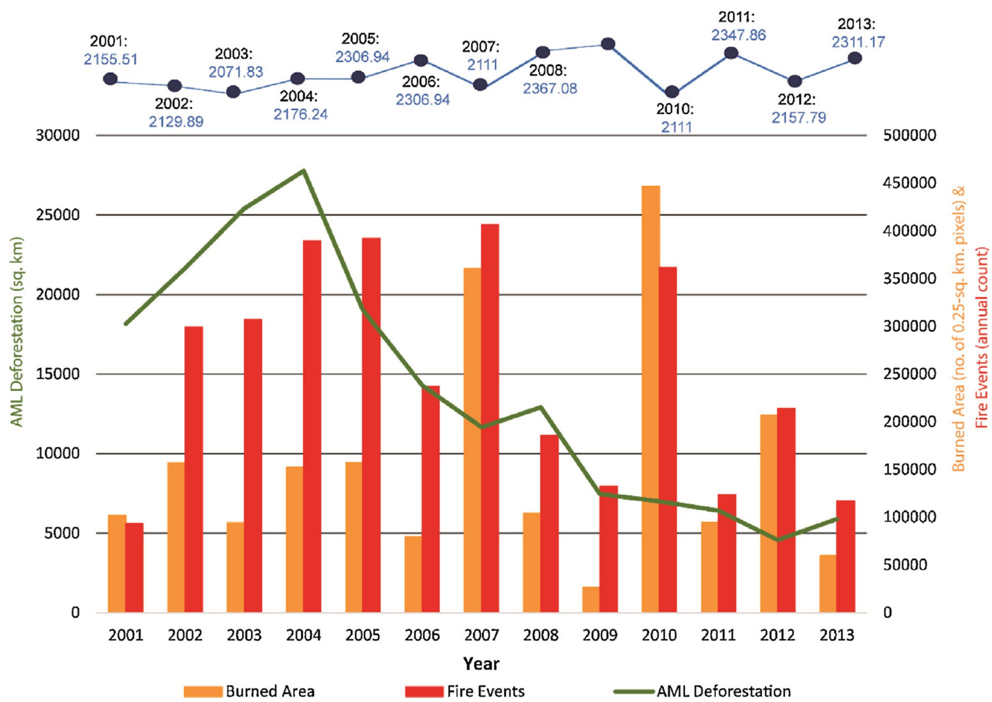

Fig. 3. Amazonian deforestation rates, TRMM average annual precipitation (mm*pixel^{-1} per year), amount of burned area (number of 0.25-km^2 pixels), and amount of fire events (annual count), 2001–2013, Brazil. Sources: INPE, TRMM, MODIS Burned Area, MODIS Active Fire.

Table A1
This table shows the standard error *(SE)* for each variable. Asterisks indicate significant values: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Variable	Coefficients (Std Err)
Protected Area	0.00 (0.00)
TRMM	0.01 (0.00)**
Deforestation prior to 1997	0.00 (0.00)
Deforestation 1997–2000	0.01 (0.00)***
Percent Cerrado	−0.02 (0.02)
Constant	−6.98 (1.38)***

group, yielding a final sample of 724 municipalities. Table A2 in Appendix A shows the descriptive statistics of covariates before and after matching.

In the second step, we used panel regression models on the sub-sampled municipalities to assess the impact of environmental policies and rainfall variation on fire. Policies include the expansion of the protected area system and blacklisting, both found to be the most important and effective public policies in the reduction of deforestation in Amazonia (Soares-Filho et al., 2010; Arima et al., 2014). Let $fire_{it}$ denote either the number of fire events or burned area in municipality i in year $t = 2001, \ldots, 2013$. The basic model can be written as follows:

$$fire_{it} = \alpha + \beta_1 MOL_{it} + \beta_2 PA_{it} + \beta_3 SPI_{it} + \beta_4 wood_{it} + tX_i'\gamma + c_i + \mu_{it} \tag{1}$$

The variable 'municipalities on the list' (MOL) is defined as:

$$MOL_{it} = \begin{cases} 1 & \text{for municipality } i \text{ listed in year t and in all subsequent years} \\ & 0 \text{ otherwise} \end{cases}$$

Although certain municipalities were removed from the list later, we first consider the effect to last for all subsequent years because removal is contingent upon improved governance over illegal deforestation and therefore is long-lasting. In the Results section, we expand our analysis and test the dynamic effect of blacklisting and if it varies over time. Fig. 4 shows those municipalities that fall into the MOL treatment group. The variable

Table A2
Matching methods result in smaller differences in standardized error for every variable used.

	Difference of Standardized Means	
	Before Matching	After Matching
3-month SPI	0.116904	0.111926
Protected Area	−0.47789	−0.40523
Wood Extraction	−1.30755	−1.19817
TRMM	−0.15689	−0.1417
Deforestation prior to 1997	−1.74084	−1.52936
Deforestation 1997–2000	−2.32638	−2.24886
Percent cerrado	0.58531	0.536501

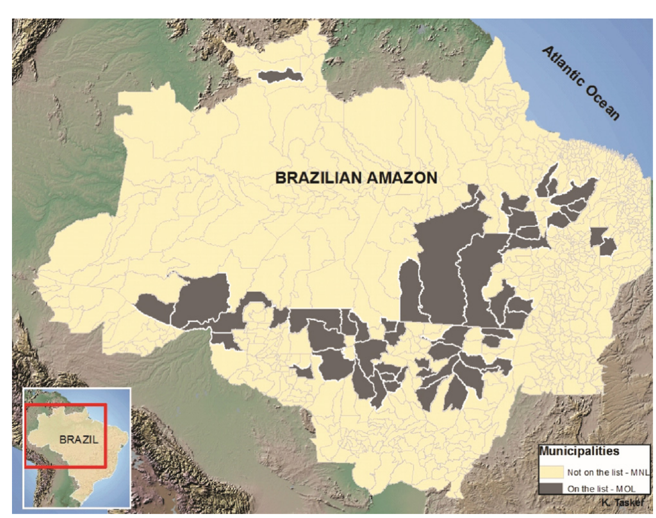

Fig. 4. Amazonian municipalities. Municipalities in gray are those municipalities that were placed on the list between 2008 and 2011, and constitute our treatment group (MOL). Untreated municipalities are shown in beige.

PA is the area under protection and includes conservation units and indigenous lands; and SPI is the standard precipitation index, a variable that captures the deviation of precipitation from the historical normal. The variable 'wood' is the volume of roundwood extracted from native forests and controls for the impact of logging on fire. The vector *X* includes time invariant variables to control for "initial conditions" (Jalan and Ravallion, 1998) in each municipality prior to 2001, the first year in the series. These variables include prior deforestation rates, long term precipitation averages, and the percent of the municipality that is cerrado, a fire-adapted tropical savanna ecoregion. The variables are interacted with t and therefore remain in the equation in fixed effects estimation procedures (see below). These initial conditions provide a strong control for factors that affect the amount of fire and that are correlated with the onset of environmental policies. Without such controls, the regression will be biased even after matching because municipalities were placed on the list precisely because of high levels of deforestation, and presumably high levels of fire (see biased regression, Table A3 in Appendix A). The vector γ contains the parameters associated with X, c_i is the municipality unobserved fixed effect, and μ_{it} denotes the error term.

Four different estimators are implemented and compared: a pooled OLS (POLS), fixed effect model (FEM), a two stage instrumental fixed effect model (FEIV), and a Hausman-Taylor estimator (HTM). The POLS assumes the composite error $e_{it} = c_i + \mu_{it}$ is uncorrelated with the observed variables. The FEM is the standard fixed effect model where the municipality unobserved effect c_i is eliminated by subtraction of the corresponding individual means. FEM leads to consistent estimators even if c_i is correlated with the observables (Wooldridge, 2010). In the FEIV, we assume MOL is endogenous and correlated with μ_{it}. We use 'deforestation until 1997' and deforestation from 1997 to 2000 as instruments for MOL. This requires the assumption that past deforestation does not directly determine fire after 2001 but is correlated with MOL (Wooldridge, 2010); a plausible assumption according to the literature (Lima et al., 2012). Finally, the HTM is based on the so called random-effects transformation. Unlike fixed effects, random-effects models can identify time-invariant effects through a stronger assumption that all regressors are uncorrelated with μ_{it}. Here we assume that MOL (time-varying) and prior deforestation (time invariant) are endogenous and SPI, percent of municipality in cerrado, and long term precipitation are exogenous.

3.1. Data processing

3.1.1. Fire events and burned area

For these analyses, our dependent variable takes two forms. The first is a measurement of fire occurrence using the MODIS Collection 5 Active Fire Data, Fire Information for Resource Management System (FIRMS) product MCD14ML. The second is a measurement of burned area using the MODIS Collection 5.1 Burned Area Data product MCD45A1, which uses Terra and Aqua satellites to identify what areas have burned on a monthly basis. While burned area can be detected by other sensors such as TM, ETM and OLI from Landsat, the information is not available for all of Amazonia for all years. MODIS is the only time-series, wall-to-wall dataset available. Additionally, while past research found that early versions of the MODIS burned area products reported considerably fewer fire detections in South America than the active fire product, the products were found to have a similar temporal pattern (Roy et al., 2008), and improvements have been made in recent years. The Collection 5.1 Global Burned Area Product improved on the previous product (Collection 5.0) by removing all MODIS band6 multi-temporal tests, which caused omission errors over certain forest and agricultural areas, and by introducing mono-temporal spectral tests to reduce burned commission errors associated with agriculture. Collection 5.1 also incorporates the Collection 5.1 MODIS land cover product, improving accuracy and resolution. The 500 m resolution pixels in the MCD45A1 dataset are each given a value of 1–4 to indicate whether the pixel was burned and with what degree of confidence the burn was detected. The "Burned Area Pixel QA" has also been refined to include QA = 5; a value indicating burned areas that are detected within an agricultural land cover class.

Because this study focuses on wild fires in forest areas, only those cells with a burned area value of 1 (most confident wildfires) were used for analysis. While a cell value of 5 indicates detections over agricultural areas, these are likely to be controlled agricultural fires for maintenance and thus were not used in our analysis. To determine the burned area for a given year, all monthly layers from the MCD45A1 were combined in a GIS into one single raster for each year were the value of the cell *i* was determined as min(BA_{jan}, BA_{fev},...BA_{dec}). MODIS FIRMS product MCD14L was also available at a monthly resolution. In this case, monthly point layers were unioned for their given year (i.e. the count of fires for all months was summed) and the number of fires in each municipality and the number of burned cells were counted using simple zonal GIS operations. The fire event data differ from the burned area data by including not only forest fires but all other types of fire such as maintenance fires on agricultural areas.

Burned area per municipality averages 40 km^2 (196 0.25-km^2 pixels) from 2001 to 2013 with a minimum of 0 km^2 and a maximum of 5,066.75 km^2 (20,267 0.25-km^2 pixels). Similarly, fire events per municipality average 288.64 events from 2001 to 2013, with a minimum of 0 events and a maximum of 7110 events (Table 1). Fig. 5 shows both burned area and fire events for every three years 2004–2013. Of the 724 municipalities used in this

Table 1
Descriptive statistics for variables of interest. For time varying variables, the number of observations is equal to the number of municipalities multiplied by the number of years for which data was available (724 × 13). In contrast, the number of observations for time invariant variables is simply the number of municipalities used in the regression. These observations indicate that the panel is strongly balanced. All values for every period across all municipalities are present in the sample.

Variable	No. of Obs.	Min	Max	Mean	Std. Dev.	Unit
Time Varying						
Burned Area	9,412	0.00	20,267.00	196.40	857.67	Total number of 0.25 km^2 pixels
Fire Events	9,412	0.00	7110.00	288.64	563.06	Number of fire events per municipality
3-month SPI	9,412	−2.93	2.53	−0.23	0.82	Number of standard deviations from historical normal
Protected Area	9,412	0.00	143,347.10	2,364.58	8,694.87	Sum of all protected areas and Indigenous areas in km^2
Wood Extraction	9,412	0.00	1,500,000.00	16,141.86	68,558.71	Wood extraction in cubic meters per municipality per year
Time Invariant						
TRMM	724	1089.40	3,454.40	1,972.30	420.82	Average mm/year for each pixel from 2001–2013
Deforestation prior to 1997	724	0.00	5,040.00	586.28	735.18	Accumulated deforestation per municipality according to PRODES (km^2)
Deforestation 1997–2000	724	0.00	533.98	59.90	106.07	Accumulated deforestation per municipality according to PRODES (km^2)
Percent Cerrado	724	0	100	23.80	36.82	Percent of the total municipality that is cerrado ecosystem (%)

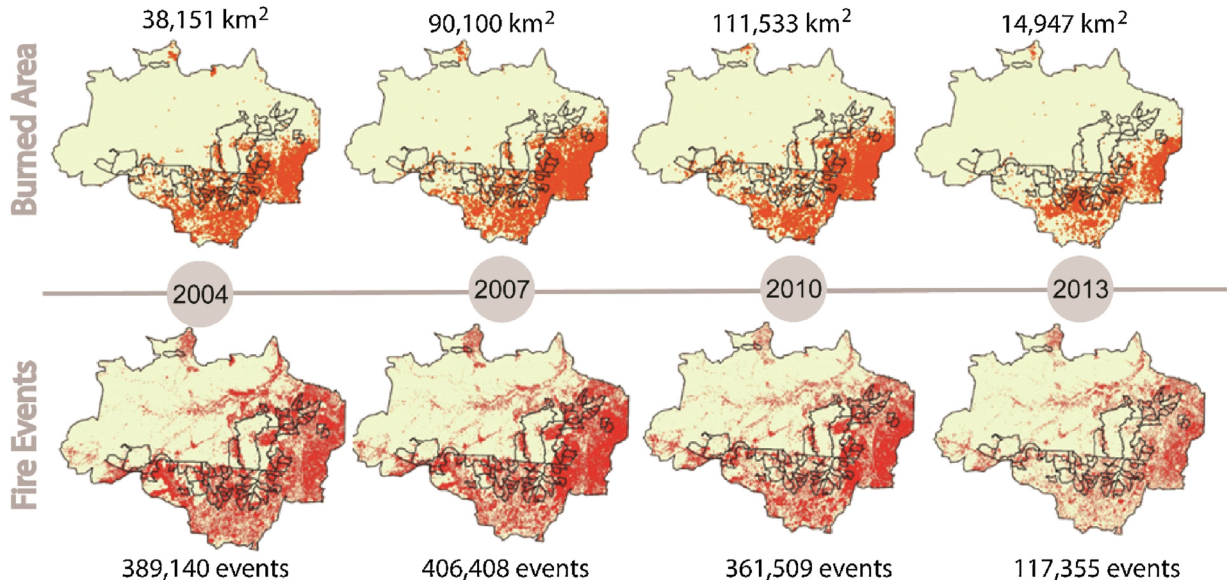

Fig. 5. Burned Area and Fire Events for the study region during 2004, 2007, 2010, and 2013. It should be noted that both 2007 and 2010 were considered drought years (see TRMM Annual Precipitation, Fig. 3).

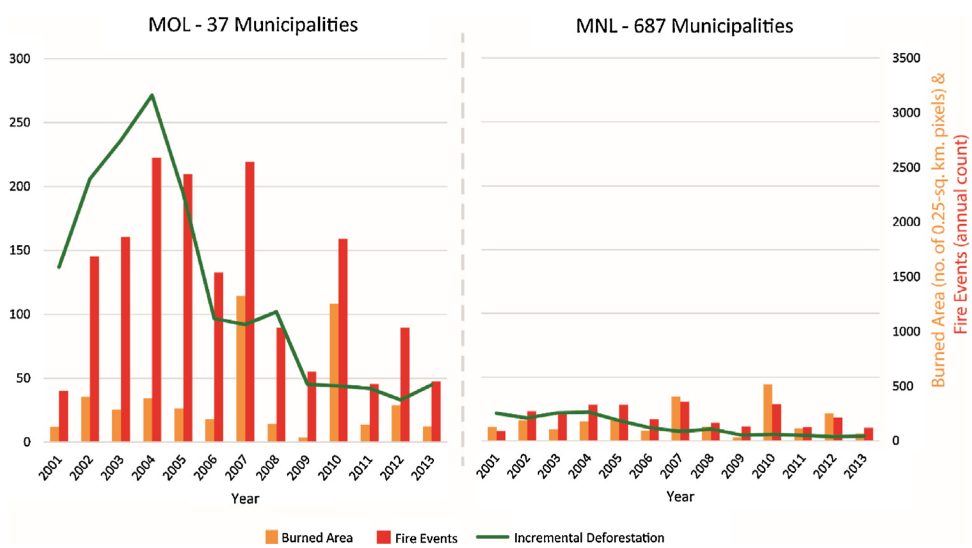

Fig. 6. A quick comparison of municipalities on (MOL) and off (MNL) the blacklist highlights the dramatic differences between the two. Here, deforestation (green line), fire events (orange bars) and burned area (red bars) are shown for both MOL and MNL counties, on shared axes.

study, 170 do not show any burned area during the period. Forty-six municipalities experienced over 1000 fire events per year on average.

3.1.2. Municipalities on the list

As described above, municipalities that underwent policy treatment are designated as MOL and are differentiated from counties that did not undergo treatment. This treatment is identified in our analyses through a binary blacklist variable. Data for the blacklist variable was obtained from the Brazilian government's Ministry of the Environment (www.mma.gov.br), which generated an annual list of counties (*Lista de Municípios Prioritários da Amazônia*) considered priorities for preventative action against deforestation in the Amazon biome (article 2 of decree 6.321/07). Employing this variable on a yearly basis not only separates the treatment group (MOL) from the untreated group, but also allowed us to account for changes in enforcement over time. These dynamic effects of blacklisting are investigated in a subsection following the presentation of main results, wherein we also present the models' details (Fig. 6).

3.1.3. Precipitation

Two types of precipitation data were also employed for our analyses: (1) TRMM product 3B43 and (2) CAMS-OPI 3-month SPI. The Tropical Rainfall Measuring Mission (TRMM) product 3B43 Version 7 reports monthly precipitation in mm/hr and combines the estimates generated by the TRMM satellite sensors, other satellite products, and CAMS global gridded rain gauge data. While this mission ended on April 15, 2015, it provided 17 years of scientific data and ultimately became the space standard for measuring precipitation. In contrast, CAMS-OPI is a precipitation estimation technique that produces real-time monthly analyses of global precipitation by combining observations from rain gauges (CAMS data) with precipitation estimates from a satellite algorithm (OPI). CAMS-OPI analyses are on a $2.5 \times 2.5^{\circ}$ latitude/longitude resolution, are updated each month, and extend back to

1979. While other datasets were available for Standardized Precipitation Indexes (SPI), the CAMS-OPI 3-month SPI was selected due to its spatial resolution and because its temporal range overlapped with the fire data (monthly resolution from 1979 through present day). The 3-month SPI compares the precipitation over a specific 3-month period with respect to the historical precipitation during that same period. For example, a 3-month SPI for the month of June 2010 shows how much the total precipitation between April, May, and June 2010 deviates from the historical total between the same April-June period.

The TRMM data was used for two purposes. First, we created a thirteen-year average rainfall value for each municipality to control for climatic variations across municipalities (time-constant variable in vector X, see above). This variable controls for the pronounced north-south and east-west precipitation gradient across Amazonia. Second, we used the TRMM to identify the driest month of the year in each municipality, which was then used to select the relevant 3-month CAMS-OPI month. This identification is important for two reasons. First, the dry and wet seasons are very distinct between the northern and southern portions of the Brazilian Amazon. In the southern part, the dry season is typically between June-September and in the northern part between December-February. Second, fire is more likely to occur during the dry seasons. Thus, by using the driest month as the identifier for the best 3-month SPI, we assume that more or less rainfall in the three months preceding the driest month of the year will have the largest impact on the overall amount of fire in a given municipality.

TRMM precipitation averages 1,972.30 mm/year from 2001 to 2013 with a minimum of 1,089.40 mm/year and a maximum of 3,454.40 mm/year (Table 1). Four-hundred eighty municipalities experienced below average TRMM during the period. Of these, 84 had averages below 1500 mm/year. In contrast, SPI averages −0.23 from 2001 to 2013, with a minimum of −2.93 and a maximum of 2.53. An SPI below −1 occurs in 16% of the samples (1619 pooled observations). Of these, nearly 70% (1090) have occurred as of 2008.

3.1.4. Deforestation

Deforestation data was obtained from the *Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite* (PRODES) dataset of Brazil's National Institute for Space Research (INPE, 2015). The PRODES deforestation dataset was used in some of our statistical analyses to account for prior deforestation conditions in both MOL and MNL counties and in our matching procedure because it was the primary criteria used for blacklisting. Although other deforestation datasets exist, we opted to use PRODES precisely because it is the "official" source of information used by Brazil's Environmental Ministry for policy implementation.[6] PRODES data is issued yearly and reports the number of hectares deforested in a given municipality. PRODES reports a gross total of deforestation per municipality up to the year 1997 (accumulated deforestation), and has annual reports of incremental deforestation from 1998 onward. Since our fire dataset begins in 2001, we used both the total accumulated deforestation until 1997 and deforestation from 1997 to 2000 in the analyses. Prior to 1997, deforestation averaged 586.28 km^2 per municipality with a minimum of 0 km^2 and a maximum of 5,040.00 km^2 (Table 1). From 1997–2001, an additional 159.17 km^2 were deforested on average per municipality, with a minimum of 0 km^2 and a maximum of 2469.12 km^2. From 1997–2001, approximately one-third (38%) of all municipalities experienced zero deforestation.

3.1.5. Protected areas

Protected Area data were obtained in GIS vector format from Brazil's Environmental Ministry website (MMA, 2015) and included information on sustainable use areas, integral protection area, and indigenous areas. Included in the attribute table were also dates when each area was created and whether it belonged to the federal or state government. This dataset was intersected with a municipality GIS vector file to determine the amount of protected areas in each municipality from 2001 to 2013. During the study period, protected areas average 2,364.58 km^2 per municipality. Of these, an average 744.50 km^2 per municipality were sustainable use areas, 468.16 km^2 were integral protection areas, and 1,162.56 km^2 were indigenous reserves. On average, 123.18 km^2 in each municipality were state-run while 344.97 km^2 were federally run.

3.1.6. Cerrado

Data for the spatial extent of the cerrado ecoregion were also obtained from Brazil's Environmental Ministry website (MMA, 2015), in GIS vector format. This dataset was intersected with a municipality GIS vector file to determine the area (km^2) and percent of cerrado for each municipality. Of the 772 municipalities, 348 are at least partially comprised of cerrado. Overall, percent cerrado averages 23.80% (Table 1).

3.1.7. Wood production

We obtained the volume of native roundwood extracted in each municipality from 2001 to 2013 from the Brazilian Institute of Geography and Statistics (IBGE) online portal SIDRA, Table 7.1 (IBGE, 2015). This is the only municipality level, time-series dataset on wood extraction in Brazil available to the general public, and includes only legal logging and wood extraction. For the study period, legal wood extraction averages 16,141.86 m^3 yr^{-1} municipality^{-1} with a minimum of 0 m^3 yr^{-1} municipality^{-1} and a maximum of 1,500,000 m^3 yr^{-1} municipality^{-1} (Table 1).

To summarize, the unit of observation for this article is the municipality (or county) and the universe for statistical analysis comprises a total of 724 municipalities after matching, of which 37 are MOL. The time dimension is from 2001 to 2013 and the panel is strongly balanced, i.e. no missing values across municipalities or time. Statistical analyses examine the impact of both the CAMS-OPI 3-month SPI and blacklisting on fire in the Brazilian Amazon. For the purposes of this article, fire is measured in terms of fire events (FIRMS MCD14ML), which include agricultural fires, and burned area (MCD45A1), which may be more representative of forest fires. Variables for past deforestation have been included in our regression equations as well.[7] In this case, past deforestation is used to control for the fact that municipalities were listed because of high deforestation in the past. Since this variable is correlated with determinants of deforestation such as roads, it also provides a good proxy for those other drivers of fire that are not included in the regression. Time constant physical attributes (soils, size of municipality, elevation, etc.) of the municipalities are controlled for in the fixed and random effects models.

[6] It should be noted that while INPE's PRODES dataset is the primary criteria for blacklisting and was selected as the deforestation dataset for this study, it is not without its flaws. Hansen et al. (2008) found that PRODES overlooked clearing of forest regrowth as a component of deforestation. Other recent studies have also highlighted the challenges associated with measuring tropical deforestation, including inconsistent results (Kim et al., 2015) and the need for a single, unambiguous definition of forest (Sexton et al., 2015).

[7] It should be noted that the data provided for past deforestation.

Table 2
Results from Pooled Orthogonal Least Square (POLS), Fixed Effects Method (FEM), Fixed Effect with Instrumental Variables (FEIV) and Hausman-Taylor Method (HTM) for both burned area (A) and fire events (B). Values indicate the coefficient for each variable, with standard error indicated by parentheses (*SE*). Asterisks indicate significant values: *p < 0.1, **p < 0.05, ***p < 0.001.

(A) BURNED AREA

Variable	POLS	FEM	FEIV	HTM
SPI	−37.09*** (10.08)	−31.62*** (7.16)	−31.90*** (7.98)	−35.31*** (7.64)
Blacklisting	41.08 (96.36)	−130.45** (64.92)	−24.28 (141.18)	−117.54** (57.22)
Protected Area	0.0044*** (0.00)	0.0011** (0.00)	0.0008 (0.00)	0.0012 (0.00)
Wood	−0.0002*** (0.00)	−0.0001 (0.00)	−0.0000 (0.00)	−0.0000 (0.00)
Deforestation up to 1997	0.1218*** (0.02)	0.0006 (0.00)	Instrument	−0.2578 (0.32)
Deforestation 1997–2000	0.4715*** (0.12)	0.0089 (0.01)	Instrument	2.1309 (1.32)
TRMM	−0.0023 (0.01)	−0.0013** (0.00)	−0.0011 (0.00)	−0.0597 (0.10)
Percent Cerrado	7.52*** (0.40)	0.1858*** (0.05)	0.1845*** (0.04)	5.799** (1.93)
Constant	−93.47** (35.87)	3,645.35*** (935.75)	4,696.12 (4074.40)	191.61 (345.09)
Number of Observations	9412			

(B) FIRE EVENTS

Variable	POLS	FEM	FEIV	HTM
SPI	−25.30*** (6.11)	−37.16*** (5.06)	−34.62*** (4.84)	−28.73*** (4.35)
Blacklisting	−31.17 (71.72)	−737.60*** (110.84)	−2,001.79*** (85.62)	−1,001.32*** (32.54)
Protected Area	0.0094*** (0.00)	0.0059* (0.00)	0.0089*** (0.00)	0.0043*** (0.00)
Wood	0.0008*** (0.00)	−0.0004** (0.00)	−0.0010*** (0.00)	−0.0003** (0.00)
Deforestation up to 1997	0.0528*** (0.01)	0.0030 (0.00)	Instrument	0.4133 (0.27)
Deforestation 1997–2000	2.52*** (0.13)	−0.1528*** (0.03)	Instrument	3.34** (1.14)
TRMM	−0.0165 (0.01)	−0.0018** (0.00)	−0.0022*** (0.00)	0.2060** (0.09)
Percent Cerrado	3.15*** (0.15)	0.0770*** (0.02)	0.0713** (0.03)	6.59*** (1.65)
Constant	24.14 (25.95)	22,173.46*** (2,003.36)	8,999.82*** (2471.15)	−708.14** (296.21)
Number of Observations	9,412			

4. Results & discussion

All statistical methods indicate a highly significant ($p < 0.001$) negative SPI impact on both fire events and burned area. For each one standard deviation decrease in SPI, burned area is estimated to increase by 31–37 0.25-km^2 pixels yr^{-1} $municipality^{-1}$ (34 pixels on average) and fire events are anticipated to increase by 25–37 events yr^{-1} (31 events per year on average) (Table 2a & b). Blacklisting had a significant ($p < 0.001$) negative effect on fire events in all models except POLS and was expected to result in a decrease of 737–2001 fire events yr^{-1} $municipality^{-1}$ (excluding POLS result, which estimates 31 additional events). In contrast, POLS showed a non-significant effect of blacklisting on both fire events and burned area, indicating that the unobservable fixed effects (such as size of the municipality, soil type, etc.) are likely correlated with the observables and therefore should be controlled for or eliminated through differencing.

Though blacklisting negatively impacted fire events, the effect of blacklisting on burned area was less clear. The POLS model found blacklisting to have a non-significant positive effect on burned area while the FEIV model found only a slight negative, non-significant impact. FE and Hausman-Taylor models found blacklisting to have a significant ($p < 0.05$) negative effect. Assuming the latter two regression models are estimating the correct effect, blacklisting would decrease burned area by 117–130 0.25-km^2 pixels per year.

Percent cerrado had a significant positive effect ($p < 0.05$ in all cases and $p < 0.001$ in most) on both fire events and burned area in all models. For each one percent increase in cerrado area, burned area is estimated to increase by up to 7 0.25-km^2 pixels per municipality per year (3.67 pixels on average) and fire events are anticipated to increase by up to 6 events per year (3.26 events per year on average). In contrast, effects of protected areas, wood extraction, TRMM precipitation, and prior deforestation on fire events and burned area remained less clear. Outside of the biased POLS model, few significant results were found. Additionally, coefficients were consistently negligible in magnitude (coefficients <0.01), indicating that even if one of the variables were found to impact fire events or burned area, they would only result in a decrease of less than 0.01 fire events per municipality, or 0.0025 km^2 of burned area per year. These minor effects were observed even when we ran different specifications of the model (results not shown but available upon request to the authors). For instance, all four models were run using lagged protected area and lagged wood extraction (t-1, t-2) to test if actions taken in one year would realize an effect in the following year or two. We also used different categories of protected areas instead of the combined total (e.g. integral protection only, state, federal protected areas) and only one prior deforestation period. Results of those models were consistent with the reported results, indicating robustness across specifications. The results seem to imply that the increment on protected areas did not have an impact on fires once you control for the other covariates. This is not to say that the overall level of protected areas does not have any impact but rather that the additional areas were not as effective, at least in the short post-implementation period. As the frontier advances into the forests and closer to newly established protected areas, those effects will be more likely to be observed in the future.

Though wood extraction is expected to be a key factor in Amazon fire, the dataset used here is based on official estimates of wood extraction and therefore does not account for illegal extraction, which may explain the lack of effect. Similarly, though SPI has a significant impact on fire events and burned area, the lack of significance of the TRMM precipitation variable may be due to the fact that we are using prior deforestation as a control. Given that prior deforestation is already correlated with gradients of precipitation (more deforestation occurs in drier areas of the Amazon), controlling for this history may confound the real effect of differences in precipitation across the region.

4.1. Dynamic effect of blacklisting

In this section, we investigate the effect of blacklisting on fire events and area burned in the five years following the time when municipalities were first blacklisted. Although we have shown in the previous section that blacklisting had a strong impact in the reduction of fire events, it is possible that this effect may have

Table 3
Results from Fixed Effect Model (FEM) including dummy variables for both burned area (A) and fire events (B). Values indicate the coefficient for each variable, with standard error indicated by parentheses (*SE*). Asterisks indicate significant values: *p < 0.1, **p < 0.05, ***p < 0.001.

Variable	FEM with Dummies	
	(A) BURNED AREA	(B) FIRE EVENTS
SPI	−29.91*** (6.78)	−36.89*** (4.98)
D^0	−233.50** (91.79)	−559.2*** (92.96)
D^1	−255.9* (143.75)	−782.8*** (148.28)
D^2	745.48** (338.35)	156.72 (163.46)
D^3	−254.3** (102.38)	−925.3*** (142.92)
D^4	−200.6** (98.77)	−549.8*** (90.78)
Protected Area	0.0009** (0.00)	0.00525** (0.00)
Wood	0.00 (0.00)	−0.00029** (0.00)
TRMM	−0.00121** (0.00)	−0.00142** (0.00)
Deforestation up to 1997	0.000522 (0.00)	0.002544 (0.00)
Deforestation 1997–2000	−0.00384 (0.01)	−0.18902*** (0.02)
Percent Cerrado	0.1865*** (0.05)	0.0761*** (0.02)
Constant	4,833.4*** (890.67)	25,623*** (1755.60)
Number of Observations	9,412	

waned over time once the impact of the first years had passed. One possible explanation for this reduced effect could be due to the lack of budgetary and institutional commitment to enforce environmental regulations once the policy was deemed "successful" after the first initial years. The alternative hypothesis is that environmental enforcement continued in the region and the impact of blacklisting is long-lasting.

To account for this dynamic effect of blacklisting, we reformulated Eq. (1) into Eq. (2), as follows:

$$fire_{it} = \alpha + D'^{k}_{it}\rho_k + \beta_2 PA_{it} + \beta_3 SPI_{it} + \beta_4 wood_{it} + tX'_i\gamma + c_i + \mu_{it}\sum_{k=0}^{4}$$

where D'^{k}_{it} is a set of dummy variables that takes the value one in k years after the municipality i was blacklisted and zero for all other years. For example, suppose a municipality i was blacklisted in 2008. Then
$D^0_{i,2001} = 0, \ldots, D^0_{i,2008} = 1, D^0_{i,2009} = 0, \ldots.; D^1_{i,2001} = 0, \ldots,$
$D^1_{i,2008} = 0, D^1_{i,2009} = 1, \ldots.; \ldots.; D^4_{i,2001} = 0, \ldots, D^4_{i,2011} = 0, \ldots.,$
$D^4_{i,2012} = 1, D^4_{i,2013} = 0.$

Thus, the coefficient ρ_k measures the effect of blacklisting k years after the municipality was blacklisted. We estimated Eq. (2) using fixed effects estimators and results are presented in Table 3.

Our results show that blacklisting had a significant impact on fire events even four years after blacklisting, with the exception of the second year following blacklisting; the coefficient $\rho_2 = 156.72$ is positive and not statistically significant. This positive effect is likely representing the confounding effect of less precipitation in 2010 since most municipalities were blacklisted in 2008 (Fig. 2). The SPI coefficient is still negative and significant despite the inclusion of the yearly dummy variable. As for burned area, the same pattern is observed: the effect of blacklisting is negative and (marginally) significant after four years of blacklisting but is positive and statistically insignificant in the second year, an indication that the dry weather in 2010 outweighed the policy effect.

5. Conclusion

While this analysis provides strong evidence for the effect of blacklisting on reducing fire events, the effect of blacklisting on burned area is not consistently negative. Considering that burned area is the variable more likely to identify forest fires as opposed to agricultural fires, these results indicate that PPCDAm-II, which has been shown to reduce deforestation (i.e. clear cutting of the forest (Arima et al., 2014)), may not be preventing forest degradation caused by wildfires in dry years.

The implications of these results could not be more important. Without addressing degradation, policies focused solely on deforestation are only partially effective. The degradation that occurs when the forest is disturbed by anthropogenic fire and logging can reduce aboveground carbon by 40% on average and constitutes an important source of emissions (Berenguer et al., 2014). Such degradation also furthers the risks of future fragmentation, burning, and grass invasion (see Fig. 1).

Climate change will likely worsen these effects (Jolly et al., 2015). Tight linkages between climate, forest flammability, and deforestation (Cochrane, 2001; Laurance and Williamson, 2001; Cochrane and Laurance, 2002, 2008; Alencar et al., 2015) as well as the strong influence of ENSO years (Alencar et al., 2004; Alencar et al., 2006; Marlon et al., 2008; Alencar et al., 2011; Alencar et al., 2015) indicate that climate will play a larger role in driving fire patterns and affecting carbon emissions in the Brazilian Amazon. Our analysis adds to this literature and provides strong evidence for the existence of a precipitation effect on fire events and burned area. Results indicate that a one standard deviation decrease in SPI could result in 11–15% more fire events and a 9–13 km^2 (18–27%)

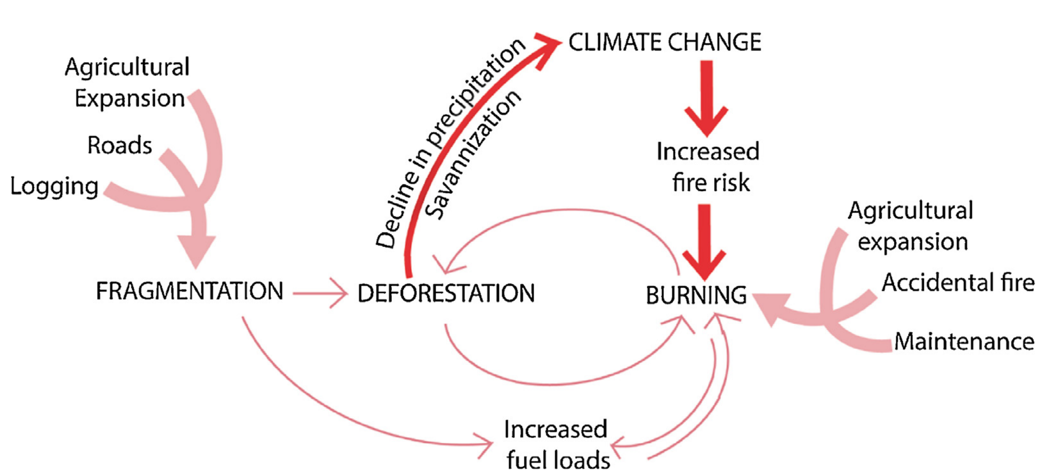

Fig. 7. Feedback between fire and deforestation, with the added components of climate change and savannization that are to come (red arrows, black text).

increase in burned area per year. Given that a one standard deviation decrease in SPI occurs in about 15–17% of the samples, the predicted decreases in precipitation are expected to have high practical significance for fires in the future.

Dry-season length over southern Amazonia has increased significantly since 1979 (Fu et al., 2013) and precipitation in Brazil is expected to further decrease in the coming decades (Sampaio et al., 2007; Fu et al., 2013). Consecutive dry years interspersed with years of only average or below average rainfall is thought to increase forest flammability, and decrease the forest's ability to resist future droughts (Alencar et al., 2011). Additionally, despite uncertainty in the spatial pattern of future rainfall shifts, climate models consistently predict that the changes will affect a large portion of tropical land (Chadwick et al., 2015). These changes are expected to be substantial, and may occur by the mid twenty-first century, continuing to intensify as global temperatures rise (Chadwick et al., 2015).

In addition to climate change driven by external forcings (e.g. CO_2), studies suggest a feedback loop between deforestation and climate that may further exacerbate the problem (Fig. 7). Regional climate models indicate that widespread deforestation may lead to declines in precipitation and consequently to the savannization of southern Amazonia and desertification of Northeast Brazil (Oyama and Nobre, 2003; Nepstad et al., 2008). Increases in deforestation are also expected to create a warmer, drier post-deforestation climate in southern Amazonia (Fu et al., 2013; Sampaio et al., 2007). These changes are likely to affect both carbon balances and future fire risk in the Amazon region (Cochrane et al., 1999; Nepstad et al., 2001; Lewis et al., 2011).

In conclusion, humans today are faced with an irony. After setting fires to non-fire-prone landscapes for years in an effort to conquer nature (Neves et al., 2004; Steffen et al., 2007; Bush et al., 2008; Glikson, 2013), anthropogenic fires in the Amazon have gotten out of our control. These anthropogenic fires may become a serious environmental challenge. The reduction of carbon emissions from deforestation and forest degradation is now a vital component in climate change mitigation strategies. Global initiatives such as REDD+ are receiving growing investments and in-country policy makers are under pressure to protect intact forests (Kollmuss et al., 2008). While Brazil met these pressures in 2009 by making the first "D", deforestation, a central piece of its climate change policy (Brasil, 2009), the initiative does not seem to have slowed the second "D", degradation caused by forest fires. This means that Brazil will likely continue to experience increased carbon emissions as well as a high rate of fire in the coming years, despite the seeming success of its deforestation reduction efforts. Even as we try to regulate these fires through policy and suppression, climate change may make efforts more costly and less effective (Nepstad et al., 2008). Brazil will face a different, drier climate in southern Amazonia in the coming decades. The Amazon, particularly its southern portion, is a place sufficiently wet to produce huge quantities of fuel (i.e. biomass) but also dry enough to allow fires to occur. As climate shifts, the area may become even more susceptible to burning. Remaining intact tropical forests may shift from being sinks of carbon dioxide and to being contributors (Lewis et al., 2011). Controlling these outbreaks and curbing carbon emissions will require innovative strategies to manage the landscape and prevent further forest degradation. This is a big task at hand that Brazil will have to address seriously in the decades to come.

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Appendix A.

Propensity score matching

We implemented propensity score matching to create a balanced sample of municipalities. This method tries to find a municipality in one group (e.g. listed) that is similar to a municipality in the other group (e.g. not listed). The procedure essentially finds municipalities that had the same chance of being listed (i.e. to receive treatment) where some were in fact listed and some were not. This is called the overlap condition in treatment effects literature. If this condition is satisfied, then the sample is said to be balanced. Similarity is established by propensity scores, which in our case is the estimated probability of being listed from a logit regression, where the dependent variable is whether the municipality was ever listed and the explanatory variables are past deforestation, precipitation, percent cerrado, and protected areas in 2001. Past deforestation is the main criteria used by the Ministry of the Environment to list or not list a municipality. We set the caliper distance to 0.093, which is the standard deviation of the estimated propensity scores multiplied by 0.55, according to the procedure advised by Austin (2011). Below we report the logit results.

Difference of means, before and after matching

This table (below) displays the difference in standardized means between listed and non-listed groups both before and after matching methods were applied. The exclusion of municipalities in one group without a counterpart in the other group within the caliper distance reduced the difference in standardized means for every variable.

Biased regression (Pooled OLS, without controls)

As can be seen below, a simple Pooled OLS, without controlling for prior deforestation rates, results in a positive effect of blacklisting on both fire events and burned area. These results indicate that if selected for policy treatment—and therefore higher enforcement of environmental laws—municipalities could expect to see an increase of over 32 km^2 (145.91 0.25-km^2 pixels) in burned area and over 586 fire events per year (Table A3, below). These spurious results are due to the fact that municipalities targeted for blacklisting were selected on the basis of higher initial rates of fire and deforestation. Without controlling for initial differences between MOL and untreated municipalities,

Table A3
Results of Pooled OLS regression, without controlling for prior deforestation. The effect on both burned area and fire events is listed. Values indicate the coefficient for each variable, with standard error indicated by parentheses (*SE*). Asterisks indicate significant values: *p < 0.1, **p < 0.05, ***p < 0.001.

POOLED OLS, NO CONTROLS		
Variable	Burned Area	Fire Events
SPI	−61.46*** (10.81)	−55.26*** (9.07)
Blacklisting	145.91* (77.59)	586.05*** (82.22)
Protected Area	0.01*** (0.00)	0.02*** (0.00)
Wood	−0.00** (0.00)	0.00*** (0.00)
TRMM	−0.35*** (0.02)	−0.23*** (0.01)
Constant	860.37*** (40.75)	676.43*** (27.60)
Observations	9633	9633

regressions remain biased and erroneously indicate that higher deforestation and fire is due to treatment.

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