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Commodity Booms, Credit Policy and The Environment

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Abstract

This paper studies how production responses from agricultural commodity booms affect greenhouse gas emissions, the primary cause of climate change. We show that Brazilian localities more exposed to booms substantially increase deforestation and agricultural fires, leading to higher emissions. The effects are significantly larger in Brazil's Amazon. Commodity booms also induce production responses toward lower emissions, such as higher output per area. Taking into account higher- and lower-emission production responses, localities present an increase in net emissions. Moreover, our findings highlight that positive economic shocks influence rural credit policy, as high-exposed localities present lower compliance with an emission-curbing credit policy — known as *Programa ABC*.

Keywords: *commodities; environment; climate mitigation policies; agriculture; ABC Program.*

JEL Classification: *Q50, Q02, O13, H81.*

1 Introduction

Understanding how the interplay between market forces and institutions can shape environmental outcomes lies at the core of contemporary policy debates. Over the past centuries, periods of economic prosperity have commonly happened to the detriment of the environment. Deforestation, intentional fires, and pollution are reoccurring examples of how human activities impact the environment. Moreover, the expected increases in population and income in many countries will likely further stress the environment. In response, climate mitigation policies have been implemented to promote behavioral responses and counteract the environmental costs associated with economic activity. These policies aim to manage greenhouse gas (GHG) emissions and, thus, are crucial to limiting the estimated increase in global temperatures.

Despite being a pressing global challenge, systematic evidence on the pathways through which economic growth affects GHG emissions or compliance with mitigation policies is rather scarce. This paper aims at filling these gaps by making two contributions. First, we provide an in-depth analysis of GHG emissions during a period of economic boom. Second, we study the interplay between market forces and institutions by assessing how economic booms affect compliance with climate mitigation policies, namely the Low-Carbon Agriculture Program by Brazil's Federal Government—*Programa ABC*.

To assess the relationship between growth and emissions, we study the effects of a strong shift in commodity prices in the 2000s and 2010s on Brazil's agricultural sector—a suitable setting to study our research question.[1] Agriculture in Brazil is an important sector of economic activity such that commodity booms can lead to substantial production responses. Besides, food production is a major driver of biodiversity loss (Dasgupta, 2021) and accounts for between a quarter and a third of the world's GHG emission over the last decades (Poore & Nemecek, 2018; IPCC, 2019; Crippa et al., 2021).[2] Furthermore, Brazil has some of the largest biomes on earth (e.g., the Amazon). Therefore, environmental preservation has consequences for the world at large and has been widely debated, with data showing significant deforestation, fires, and GHG emissions.

Do commodity booms always come at an environmental cost? Conceptually, production responses to commodity booms can generate net-positive, net-zero, or net-negative GHG emissions. Deforestation and fires, for instance, are *carbonizing factors* as they are associated with net-positive emissions.[3] By changing production incentives, booms may lead to deforestation and fires in new and existing agricultural areas. Alternatively, booms may increase production intensity, which would lead to less GHG emissions (*decarbonizing factors*). Finally, some production responses have an intrinsically ambiguous effect. Booms change relative prices (i) between crops and livestock and (ii) within crops (crop mix). Cattle-raising and selected crops (such as rice, sugar, and cocoa) are among the largest GHG emitters. Therefore, if booms lead to land-use conversion away from livestock

[1] The commodity boom we study is a period of sustained demand for agricultural and mineral commodities led by China and other countries. For more details, see Appendix B.

[2] Food production is estimated to use up to half of the world's habitable land and 70% of global freshwater.

[3] Although countries (including Brazil) legislate against the use of fires, agricultural producers using fires to clear land and promoting deforestation is a pervasive feature in many countries.

and toward a lower-emission crop mix, it would lead to less GHG emissions. Since carbonizing and decarbonizing factors generate conceptually ambiguous effects, the environmental impacts of commodity booms is thus ultimately an empirical analysis and context specific.

Using a shift-share design, we construct a commodity exposure index for each municipality in Brazil.[4] The exposure index uses the (plausibly exogenous) time-series variation of international commodity prices and the spatial variation in agricultural suitability. We start by showing that localities more exposed to the commodity boom increase production and land demand, as measured by increases in agriculture Gross Domestic Product (GDP) and total production area. Using satellite data, we find that greater commodity exposure generates measurable impacts on deforestation and fires. Specifically, the elasticity of deforestation and fires with respect to the commodity exposure index is about 0.5 and 0.2, respectively.

To further understand the role of carbonizing and decarbonizing factors, we assess the impacts on production intensity, land-use conversion, and crop mix. Decarbonizing factors play a chief role: we find greater intensity in crop production and land allocation toward a lower-emission crop mix. By contrast, we also find an increase in land allocation toward cattle raising, an important carbonizing factor. Taken together, these different margins of adjustment indicate an ambiguous effect on GHG emissions. Our results highlight an important point: one needs to consider the multiple ways commodity exposure affects conservation to assess the overall environmental impacts.

To measure the net effect of the commodity boom, we gather novel data on GHG emissions combining satellite and field-collected data. Carbonizing factors (namely, deforestation, fires, and cattle raising expansion) dominate as localities more exposed to the commodity boom present an increase in net GHG emissions. Moreover, net emissions increase less than gross emissions, consistent with the role of decarbonizing factors we study. A heterogeneity analysis indicates that the effects of commodity prices on deforestation, fires, and GHG emissions are significantly higher in the Amazon and the Cerrado—Brazil's major biomes.

We perform different robustness exercises and specification tests following the advances of the shift-share design literature (Goldsmith-Pinkham, Sorkin, & Swift, 2020 and Borusyak, Hull, & Jaravel, 2021). For instance, the differential effects are not observed outside our period of analysis as more heavily exposed localities do not trend differently with respect to environmental outcomes. The results are robust to several additional analyses, such as alternative definitions of commodity exposure, inclusion of various types of control variables, multiple hypothesis correction, different sets of specification, and alternative standard errors' clustering.

Our second contribution is to assess how commodity booms affect compliance with climate change mitigation policies. The importance of these policies is not specific to Brazil: mitigation falls short of intended goals, and many governments worldwide have been implementing policies to incentivize mitigation (UNEP, 2019). More specifically, we investigate how commodity exposure affects compliance with the ABC ("*Agricultura de Baixo*

[4] Brazil's municipalities are autonomous administrative entities roughly equivalent to U.S. counties.

Carbono") credit program: a chief initiative to boost sustainable economic practices to reduce the country's carbon footprint. As part of Brazil's commitment to multilateral cooperation to cut emissions, the ABC credit program offers subsidized credit lines for farmers and livestock producers to boost environmentally-friendly management practices in agriculture.[5] Our findings indicate that areas more exposed to the commodity boom increased overall credit (consistent with the increase in GDP we find) but reduced the amount of ABC credit. The results suggest then that high-exposed localities present lower compliance with this emission curbing policy. Next, we present suggestive evidence of potential mechanisms which could be underlying these novel findings. The effect seems to be driven by a lower adoption of environmentally-friendly management practices in high-exposed localities, precisely the program's focus.

Our paper relates to several strands of the economics literature. We first connect to the extensive literature on the effects of economic growth on environmental outcomes (e.g., Grossman & Krueger, 1995, Panayotou, 2000, Foster & Rosenzweig, 2003) and, more recently, to research on the impacts of economic activity on climate change (Stern, 2008; Nordhaus, 2019).[6] Our work pushes this literature forward by providing a systematic exploration of net GHG emissions after considering a broad set of (market-driven) carbonizing and decarbonizing factors. In addition, among this literature, this paper is unique in showing that economic booms can further lead to environmental deterioration by affecting the effectiveness of policy-driven mitigation.

We also relate to the literature on climate mitigation policies. Importantly, studies suggest that, while legislation may be an effective way to put policies in place, voluntary compliance with climate policies usually tends to be ineffective (e.g., Haug et al., 2010; Eskander & Fankhauser, 2020; Fekete et al., 2021).[7] In particular, we are closely related to the literature diving into the relationship between credit policies and deforestation (e.g., Assunção, Gandour, & Rocha, 2015; Assunção, Gandour, Rocha, & Rocha, 2020; Harding, Herzberg, & Kuralbayeva, 2020). We contribute by showing an unintended consequence from booms: lower compliance with climate mitigation policies. Our paper also adds another piece of evidence by examining a potential mediator (management practices) explaining the lower compliance with the emission curbing policy. These findings have far-reaching implications for different topics beyond conservation by highlighting how a macroeconomic context interferes with externality-reducing policies.

Finally, we connect to the literature on the causes and consequences of deforestation and fires (e.g., Barona, Ramankutty, Hyman, & Coomes, 2010; Andela et al., 2017; Bragança, 2018; Balboni, Burgess, Heil, Old, & Olken, 2021; Balboni, Burgess, & Olken, 2021). To our knowledge, we are the first to investigate the effects of economic booms on fire outbreaks.

[5]The credit funds low or net-zero GHG-emission management practices such as the conversion of degraded pasture land, implementation of commercial forests, and animal waste treatment systems. It also funds machine and equipment purchases if they are related to sustainable practices in agriculture. For more details on the ABC Program, see Appendix B.

[6]We also connect to the literature investigating the effects of natural resource booms on local economic growth (e.g., Caselli and Michaels 2013; Allcott & Keniston, 2018; Cavalcanti, Da Mata, & Toscani, 2019).

[7]In addition, studies indicate that conservation policies may not affect the economy (e.g., Koch, zu Ermgassen, Wehkamp, Oliveira Filho, & Schwerhoff, 2019).

This is important because biomass burning is a significant contributor to emissions (Wake, 2021). Our study is closely associated with the branches on the impacts of trade shocks and agriculture expansion on deforestation (e.g., Pfaff, 1999; Cattaneo, 2002; Burke & Emerick, 2016; Faria & Almeida, 2016; Chen, Chen, & Xu, 2016; Zhang, Zhang, & Chen, 2017; Assunção, Lipscomb, Mobarak, & Szerman, 2017; Dornelas & Chimeli, 2019). We complement by studying GHG emissions (a worldwide negative externality) related to deforestation and fires.

The remainder of this paper is organized as follows. Section 2 describes the empirical strategy, while Section 3 presents the data. Section 4 shows the results. Section 5 concludes.

2 Empirical Strategy

Our empirical strategy is a shift-share design, which combines time-series variation from international commodity prices and cross-section variation from agricultural suitability. The spatial (cross-section) unit of analysis is the municipality (5,570 units), and our yearly data span from 2001 to 2017. We estimate the following empirical specification:

$$y_{it} = \mu_i + \delta_t + \beta CE_{it} + \gamma X_{it} + \eta_t W_i + \varepsilon_{it} \quad , \tag{1}$$

where y_{it} is the environmental outcome of interest for municipality i at year t, μ_i stands for municipality fixed effects, and δ_t stands for time fixed effects. Our set of dependent variables includes carbonizing and decarbonizing variables. We add the unit fixed effects μ_i to control for municipality unobserved fixed determinants and time fixed effects δ_t to control for aggregate shocks common to all units at a specific moment in time. The vector X_{it} includes time-varying geo-climatic variables, and W_i is a set of socioeconomic variables. All municipalities have equal weights. In addition, standard errors are clustered at the municipal level since the variation we measure occurs at the municipal level, and errors may be correlated within the spatial units.

Our primary interest is in the coefficient β, which represents the response of our dependent variables with respect to the commodity exposure index CE_{it}. Let k denote a given crop or livestock. The commodity exposure index for municipality i and time t is defined as the inner product of the initial shares and commodity prices as follows:

$$CE_{it} = \sum_k q_{ki} P_{kt} \tag{2}$$

where the term q_{ki} is the share of total production (in tons) for crop or livestock k pre-commodity boom, which sums up to 1 across a given k. We use data from the years 1996–2000 to fix the share variable (using the average share for the period). P_{kt} is the real international commodity prices for crop or livestock k at time t.

The identifying assumption of our exposure design is that municipalities would have had similar environmental outcomes in the absence of the commodity boom. Intuitively, our empirical approach asks whether municipalities with a greater increase in commodity exposure—e.g., places in which the increase in international prices matched their pre-boom commodity specialization—experienced a different trajectory when it comes to environmental outcomes. Given our research question and that the empirical strategy uses heterogeneity in municipalities' exposure to different commodities, the identifying assumption based on shares is more natural (Goldsmith-Pinkham et al., 2020 and Borusyak et al., 2021). The shift variable (international commodity prices) is, however, assumed to be exogenous to local conditions. The shift component (commodity price) increase in our period of analysis was triggered by the sustained demand for agricultural and mineral commodities by China and other countries that are likely to be independent and not driven by local conditions of a particular municipality.

Even though the lagged, fixed quantities for the share variable aims to reduce endogeneity concerns, we provide several specification checks on the plausibility of the identifying assumption (Goldsmith-Pinkham et al., 2020). Moreover, in the robustness exercises, we use two alternative measures of commodity exposure, which employ other fixed cross-sectional exposure variables. Following Benguria, Saffie, and Urzúa (2021), the first alternative commodity exposure index substitutes the lagged quantity shares q_{ki} in Equation (2) by pre-boom employment shares. Following Fiszbein (2021), the second alternative index uses the FAO-GAEZ climate-based potential yields, which are based on exogenous geo-climatic features—like weather and soil characteristics. The second alternative index substitutes the quantity share q_{ki} in Equation (2) by the "predicted" quantity shares, which consists in instrumenting for the lagged quantities shares by using the FAO-GAEZ potential yields. See Appendix C for a detailed description of the two alternative measures.

Standard error clustering in shift-share designs could result in over-rejection due to the possibility of shares being similar among regions with similar sectoral structures.[8] Hence, in the robustness exercises, we cluster the standard errors at the more aggregated spatial units to account for cross-regional correlation. We also follow Adão, Kolesár, and Morales (2019), who developed inference methods that are valid under cross-regional correlations. In addition, we perform an inference assessment following Ferman (2021) to alleviate concerns on the standard errors clustering as over- and under-rejection of the null is typically a concern in shift-share designs.

In the interest of full disclosure, we present the effects with and without controls and show similar results. To report our baseline results, we use the natural logarithm transformation in Equation (1) for the dependent and commodity exposure variables. In Appendix A, we show the results using the inverse hyperbolic sine transformation ($asinh$) on these variables.

Finally, we applied multiple hypothesis corrections within "families" of outcomes, reporting usual p-values in the main analysis and p-values adjusted for correction in the robustness section. More precisely, we use Holm (1979)'s family-wise error rates correction.

Panel (a) of Figure 1 depicts the 12-month-moving average of commodity prices, crop prices, and beef prices. Panel (b) displays the baseline commodity exposure index for 2010. One may notice the relevant increase in commodity prices that took place during our period of analysis. In addition, exposure to the commodity shock seems to be widespread

[8]Such similar sectoral structures are present in our setting. For example, municipalities in Mato Grosso state could have similar shares to municipalities in Paraná state, two heavily dependent soybeans-and-maize-production regions.

across Brazil's municipalities. Finally, to motivate the analysis, Panel (c) illustrates the time-series evolution of GHG emissions. We focus on the top and bottom parts of the commodity exposure index distribution: the 25% more exposed municipalities increased emissions over time, while emissions for the 25% less exposed localities remained flat. The fact that municipalities in the top and bottom parts present a different pattern motivates a more systematic investigation of the role of booms in guiding emissions.

3 Data

We use comprehensive data to assess the environmental impacts of commodity booms.

Greenhouse Gas Emissions. Data on GHG emissions and removals ("sinks") are from the Climate Observatory's SEEG (in Portuguese, *Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa*)—see de Azevedo et al. (2018). GHG emissions and removals are estimated for all Brazilian municipalities combining satellite and field-collected data. Greenhouse gases include carbon dioxide (CO2), methane (CH4), nitrous oxide (N20), and other gases (e.g., perfluorocarbons, hydrofluorocarbons, sulfur hexafluoride, and nitrogen trifluoride). Emissions are calculated for a wide range of activities, such as enteric fermentation of ruminant animals, burning crops, soil fertilization, changes in land cover, burned forest residues and liming, fuel combustion, and manufacturing activities. GHG removal is a process through which greenhouse gases are withdrawn from the atmosphere, and are calculated from land-use changes and other sources of carbon sequestration, such as forest plantation and better agricultural management practices. For each municipality, we obtain data on total GHG emissions (henceforth gross GHG emissions) and total GHG emissions subtracting total removals (henceforth net GHG emissions). From the list of emitter activities, we collect data on (i) GHG emissions for the agriculture sector and (ii) GHG emissions from changes in land use.

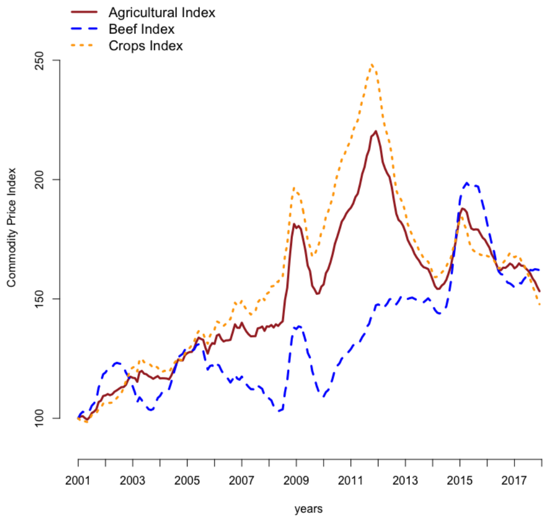
Number of fires. Satellite data on fires is from the National Institute for Space Research (INPE) fire dataset (in Portuguese, *Banco de Dados de Queimadas*)—see INPE, 2020a. A reference satellite collects detailed (daily) images of fires of at least 30-meter long by 1-meter wide for each pixel of one square kilometer.[9] The satellite data allow for comparisons among municipalities over time.[10] We aggregate the pixel-level fire counts to calculate the number of fires at the municipality-year level.

Deforestation. Satellite data on deforestation is from INPE's PRODES for municipalities in the Amazon biome and INPE's Terrabrasilis for municipalities in the Cerrado biome—See INPE, 2021a and INPE, 2021b. The Amazon and the Cerrado represent approximately 73% of country's territory. These two databases measure the yearly deforested area in square

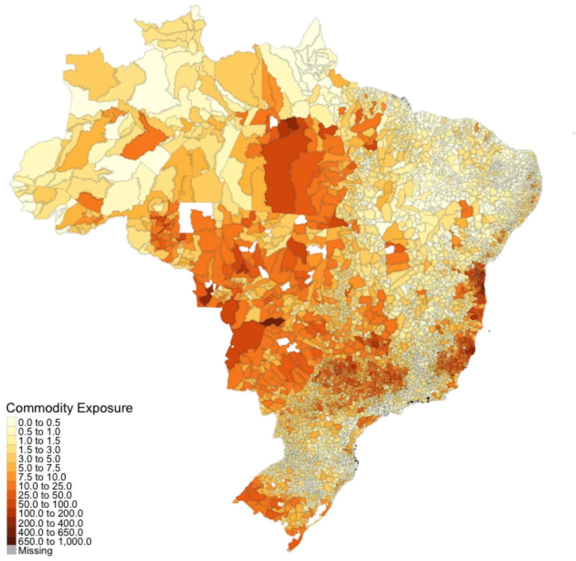
[9] A fire inside a pixel is counted as "one fire" whether its size is equal to the minimum detectable area (30-meter length by 1-meter width), one large fire of about one square kilometer, or several medium-sized fires. If a fire surpasses one square kilometer, the fire count will equal the number of pixels it occupies (INPE, 2020b).

[10] Between June/1998 and July/2002, the reference satellite was NOAA-12 with sensor AVHRR, which captured images at the end of the afternoon. From July/2002, the reference satellite is the AQUA_M-T with sensor MODIS, which captures images at the beginning of the afternoon.

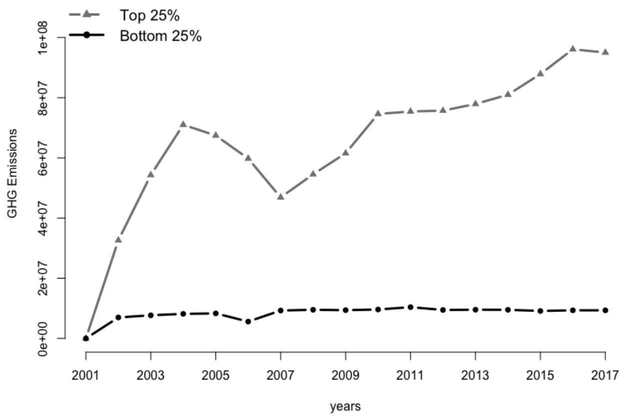
Figure 1: Commodity Prices, Exposure Index, and GHG Emissions



(a) Price Index (12-month moving average)



(b) Commodity Exposure Index (2010)



(c) Top versus Bottom: GHG Emissions

Notes. Panel (a) presents the price index for the selected commodities we utilize in the exposure index. Panel (b) shows the commodity exposure index for year 2010. Panel (c) presents GHG index, which corresponds to the the difference of greenhouse gas emissions (in tons of CO2eq.) in agriculture between each year (from 2001 to 2017) and first year of analysis (2001) for the 25% most and 25% least exposed municipalities in our sample. By construction, this GHG index is zero in 2001. Data on prices come from the World Bank and FRED; data on the commodity exposure index stem from the World Bank and IBGE and is further described in Section 2. GHG emission data is from Brazil's SEEG from the Climate Observatory.

kilometers for each municipality. For municipalities in the Cerrado biome, Terrabrasilis collected data every two years between 2001 and 2012 (official data fill the gap years by replicating the previous year's information in the database), and yearly from the year 2013 on.

Rural Credit. To obtain credit information, we gather monthly data on rural credit from the *Matriz de Dados do Crédito Rural* from the Central Bank of Brazil. The data is at the municipality-year level. To be precise, data allow us to disaggregate the credit data into two categories: (i) total credit of rural producers for investments in machines, equipment, and other materials; and (ii) ABC ("*Agricultura de Baixo Carbono*") credit for sustainable agricultural investments and management practices. See Subsection 4.4 for more details on the ABC program. The credit data is only available for the period from 2013 to 2017. All nominal variables are set to 2010 constant (real) values.

Commodity Exposure Index. The baseline commodity exposure index uses two datasets from the Brazilian Bureau of Statistics (IBGE): *Pesquisa Pecuária Municipal* (PPM) and *Pesquisa Agrícola Municipal* (PAM). We collect information on crops and livestock (in tons and number of heads, respectively) produced in every municipality from 1995 to 2019. We select the following crops and livestock: rice, sugarcane, maize, soybeans, banana, cocoa, coffee, orange, and bovines.[11] The selection includes temporary crops, permanent crops, and livestock based on their importance in total production—they represent approximately 80% of agricultural production value per year, according to IBGE's PAM and PPM—and their widespread cultivation across Brazil's regions, as shown in Appendix Table A.2.[12] In addition, we set the commodity exposure index to 2010 constant (real) values using international commodity prices in US dollars from the World Bank (The Pink Sheet), Brazil's consumer price index (IPCA index), and exchange rate data from Ipeadata. Finally, we collect employment data from the 1995 agricultural census and FAO-GAEZ soil-and-climate productivity measures for the alternative commodity exposure indexes. See more details in Appendix C.

Agricultural Census. We also use data from IBGE's agricultural censuses of 2006 and 2017 on the number of tractors in farms, area used for crops, area employed as rangeland (natural, degraded, and good pastures), the number of agricultural implements such as harvesters, seeders, and fertilizers in farms, irrigated area in farms, no-till-cultivated areas, and land allocated as good-pastures.

Additional data. We now describe the data used in the control vectors of our empirical specification. IBGE provides data on the yearly population counts for each municipality,

[11] Our definition of $\sum_k q_{ki}$ for bovines includes all bovines in cattle production, so entails the "stock" of bovines (young cattle being raised) and the current flux of bovines for meat processing. Brazilian livestock producers usually specialize in certain stage-of-life bovine: some breed and raise calves up to weaning, others fatten up weaned cattle, while others confine them for meat processing. Commercial transactions are common among these specialized ranchers—meaning the flux and the "stock" of bovines are relevant. The same is not valid for crops, once farmers cannot specialize in growing just a one-stage-of-life culture.

[12] We transform the number of heads of cattle in tons using 230 kilos for the average bovine, considering a conservative estimate on the bovine carcass in Brazil (IBGE, 2019). We also transform the number of banana bunches and oranges to tonnes according to IBGE (2020).

while data on latitude, longitude, temperature, and rainfall comes from Da Mata and Resende (2020). The set of demographic data—such as unemployment rates, illiteracy rates, the percentage of poor individuals, and urbanization rates—for each municipality in 2000 is from the United Nations Development Programme's *Atlas do Desenvolvimento Humano dos Municípios*.

Table A.1 in Appendix A shows the summary statistics for our variables of interest, including the commodity exposure indexes.

4 Results

We divide the results into five parts. First, we study the effects of commodity booms on economic activity, deforestation, and fires. Second, we discuss the role of additional carbonizing and decarbonizing factors focusing on production responses related to productivity, land use, and crop mix. Third, the overall impacts on GHG emissions are analyzed. We then analyze how booms affect climate mitigation policies—the ABC program. We finish with further analyses, including the results on the Amazon biome and robustness checks.

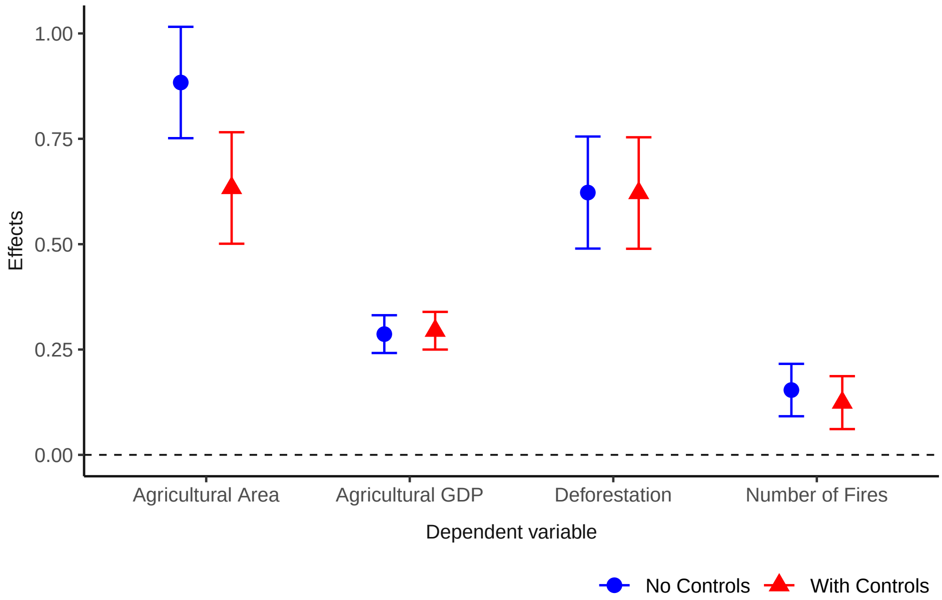
Our results are shown in Figures 2 through 7. Our figures follow a common format. Each plot presents the coefficient of interest and the confidence intervals from estimating Equation (1) with a different set of controls. In the interest of space, the figures only report the results of the baseline commodity exposure and the natural logarithm transformation. In the online Appendix A, we present the tables with the results when we analyze other commodity exposure measures and use the inverse hyperbolic sine transformation.

4.1 Effects on Economic Activity, Deforestation, and Fires

We start by showing the effects on economic activity. Figure 2 shows the results for agricultural area and agricultural GDP. Localities more exposed to the boom present an increase in both agricultural GDP and area. More precisely, a 1% rise in exposure leads to a 0.3% increase in agricultural GDP and 0.6% rise in pasture and cropland measured in hectares—when considered with controls. The increase in the agricultural area we observe is consistent with greater land demand from the boom period. Besides, the increase in GDP is consistent with (i) the greater land (input) use, (ii) production responses from higher international commodity prices, and (iii) the (mechanical) influence of the higher commodity prices in the GDP calculation. Figure 2 also documents an increase in deforestation and fires in high-exposed localities: an increase of 1% in commodity prices generates approximately 0.6% more square kilometers of deforestation and 0.12% more fires.

Recall that the deforestation data are only for municipalities in the Amazon and the Cerrado. These biomes have been undergoing the expansion of agricultural activities over the last decades. The relevance of our results resides in showing that commodity booms are related to the economic expansion of the agricultural sector with further impacts on deforestation and fires. These are strong *carbonizing* effects of commodity booms. These fires are likely related to land-clearing for livestock purposes, which we discuss in details in Subsection 4.5.

Figure 2: Effects of Commodity Booms: Economic Activity, Deforestation, and Fires



Notes. This figure presents the results from the estimation of Equation (1) for four dependent variables: Agricultural Area, Agricultural GDP, Deforestation, and Number of Fires. The unit of observation is municipality-year. Agricultural Area is the sum of pasture and cropland in hectare. Agricultural GDP is deflated to 2010 Brazilian *reais*. The change in yearly deforestation is measured in squared kilometers, and the number of fires is the yearly count. Dependent variables and the commodity exposure index are transformed into $log + 1$—see Appendix Table A.18 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

4.2 Effects on Carbonizing and Decarbonizing Factors

Beyond deforestation and fires, production responses from commodity booms can lead to further GHG emissions or lead to "market-driven" environment-friendly mitigation. In Figure 3, we assess the role of land-use conversion between crops and livestock. The estimates show that pastureland share increases by 0.14% as a share of total farmland, given a 1% percent increase in exposure. Since we define farmland as the sum of cropland and pastureland, the crop share area mechanically decreases by the same amount. Cattle raising is often associated with higher greenhouse-gas emissions, so our findings suggest that changes in land use lead to further GHG emissions.

We then analyze the effects on production intensity. Figure 3 reports that livestock productivity—measured by the counts of cattle over hectare allocated to pastureland—has decreased in areas more exposed to the commodity booms. This is consistent with the idea that rising prices generate an incentive for area expansion, which takes place by increasing pastureland—thus reducing productivity per hectare since cattle heads generally do not keep pace with such area expansion.

By contrast, we find that crop productivity (crop production per hectare) has directly increased. Results also indicate that an indirect effect through capital demand has also taken place as measured by an increase in the number of tractors per hectare. A 1% increase in commodity prices is related to a 0.43% increase in tractors per hectare. This result suggests that farmers also increase their demand for capital by investing more in tractors per hectare of land due to the increasing commodity prices. As a result, the production intensity in crops leads to lower emissions. The increase in capital demand suggests a complementarity between land and capital in the production function for agricultural outputs (recall the increase in land demand we find in Subsection 4.1).

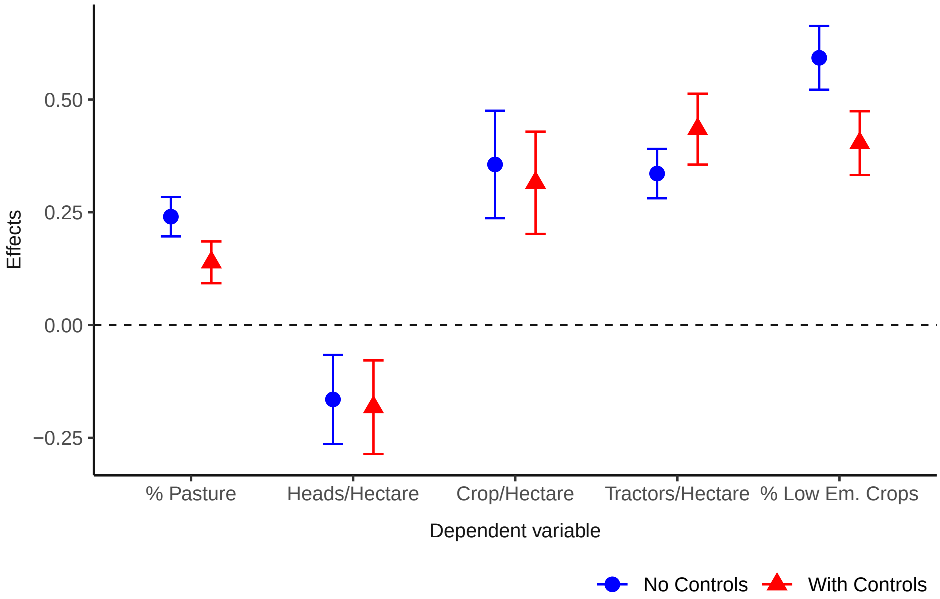
Finally, we inspect the role of crop mix. Our results indicate that there has been crop reallocation from higher- toward lower-emission crops. Following a classification of GHG emissions by each crop from Poore and Nemecek (2018), we find that more land as a percentage of total cropland was allocated towards lower-emission crops. Soybeans, orange, maize, coffee, and bananas are considered low-emission crops as their estimated global variation in GHG emissions, land-use, terrestrial acidification, eutrophication, and scarcity-weighted freshwater withdrawals are considered relatively low (Poore & Nemecek, 2018). Rice, sugarcane, and cocoa, however, are considered higher-emission crops. Results in Figure 3 suggest that a 1% increase in commodity prices generates a 0.40% rise in cropland allocated toward lower-emission crops.

Taken together, the analysis of land use, productivity, and crop mix shows that the commodity boom generated production responses leading to higher emission as well as promoting mitigation.

4.3 Effects on GHG Emissions

We now turn to the broad implication of commodity booms for net greenhouse gas emissions. We run our baseline Equation (1) with four different measures of GHG emissions as dependent variables: (i) total (gross) emissions, (ii) emissions from the agriculture sector,

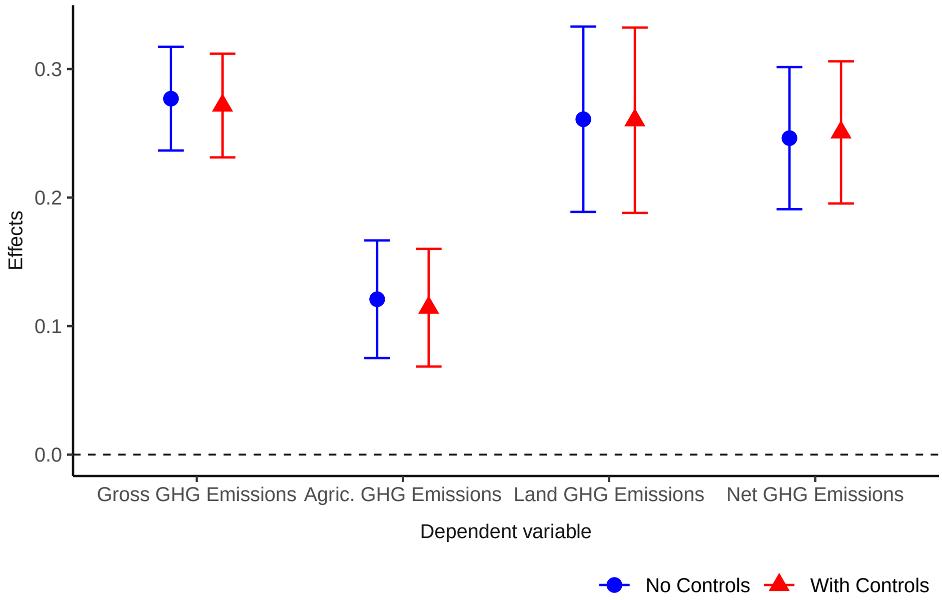
Figure 3: Effects of Commodity Booms: Land Allocation, Crop Mix, and Productivity



Notes. This figure presents the results from the estimation of Equation (1) for five dependent variables: % of Pasture Land, cattle Heads per Hectare, Crop production per Hectare, Tractors per Hectare, and % of Low Emission Crops. The unit of observation is municipality-year. % of Low Emission Crops is the area in percentage taken by crops that emit less greenhouse gases, and % of Pasture Land is the area in percentage of natural, well-managed, or degraded pasture. Crop production per Hectare is in tons per hectare, and cattle Heads per Hectare and Tractors per Hectare are the count of heads and tractors divided by hectare, respectively. Dependent variables and the commodity exposure index are transformed into $log+1$—see Appendix Table A.19 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

(iii) emissions from land-use changes, and (iv) net emissions, which subtract GHG sequestration by multiple sources. Figure 4 reports that high-exposed localities present higher gross, agricultural, and change in land-use emissions. In addition, after taking into consideration carbonizing and decarbonizing factors, net emissions increase in high-exposed localities.

Figure 4: Effects of Commodity Booms: Greenhouse Gas Emissions



Notes. This figure presents the results from the estimation of Equation (1) for four dependent variables: Gross GHG Emissions, Agricultural GHG Emissions, Change in Land Use GHG Emissions, and Net GHG Emissions. The unit of observation is municipality-year. Gross and net GHG emissions are measured in tons of CO2eq. for each municipality, while agricultural and change in land use are measures for their respective sectors in the same unit. Dependent variables and the commodity exposure index are transformed into $log+1$—see Appendix Table A.20 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

GHG emissions rise about 0.27% with a 1% increase in exposure to commodity booms, reflecting Brazil's large agricultural and agribusiness sectors and their spillovers in the economy. In addition, emissions from agriculture have a smaller magnitude with respect to prices, while land-use emissions are shown to be more responsive. This partially reflects our results in the previous subsections since agricultural activities present some mitigation from production responses (such as land allocation toward low-emission crop mix), whilst the land-use results demonstrate that commodity prices strongly impact deforestation and fires.

4.4 Impacts on Climate Mitigation Policy — ABC Program

This subsection assesses how the commodity boom has impacted voluntary compliance with a climate change mitigation policy. In 2010, the Brazilian national government implemented a program seeking to reduce GHG emissions in agriculture: the *Agricultura de Baixo Carbono* (ABC) Plan.[13] The program provides subsidized credit for low or net-zero GHG-emission management practices and investments in farming and livestock. The credit program finances several production techniques such as no-till planting, conversion of degraded pastureland into productive pasture or crops, implementation of integrated systems (crops, livestock, and planted forests), implementation of commercial forests, and animal waste treatment systems. Other areas could also be financed—such as equipment, machinery, and production-related infrastructure—but only if related to environmentally sustainable practices (MAPA, 2016). For more details on the ABC Program, see Appendix B.

Since the program started in 2010, we perform the analysis for a different period. More precisely, we analyze the impact of booms on the ABC program for the period 2013–2017 due to data restrictions (see Section 3). Credit data, for instance, are only available for 2013 on. Therefore, we calculate the commodity exposure index in Equation (2) using the average quantity share for 2008–2012. As a consequence, we analyze a period of relatively lower crop prices, but increasing beef values (recall Figure 1a).

Figure 5 displays the results. On the one hand, total credit augments approximately by 0.28% as a response to a 1% increase in exposure. On the other, the ABC credit line was negatively impacted: a -0.29% change as a response to a 1% increase in commodity exposure. Although interest rates for the ABC credit were consistently lower than traditional lines during 2013-2017 (Vieira Filho & da Silva, 2020), producers' take-up of ABC credit line was negatively associated with exposure. One implication from our results is that macroeconomic variables can affect voluntary compliance with climate mitigation policy.

We perform two exercises to understand our results further. In the first exercise, we explore the potential role of management practices to provide suggestive evidence on the channels underlying our findings. Data from the agricultural census of 2017 provide detailed cross-sectional information and allow us to study two practices in farming and livestock: no-till farming and proper pastureland management.

No-till farming is an agricultural technique for planting and growing crops without tilling ("disturbing") the soil. In this system, seeds are planted over the residues of previous crops by planters that cut a V-slot, place the seeds, and close the furrow. This technique does not provoke the rotting of organic matter in the soil, avoiding the release of greenhouse gases. In addition, planting over the residues of past crops/pastures can retain more water and nutrients, while organic matter (CO_2) in the soil also increases.

Areas with proper management practices to improve pastureland ("well-managed pastureland") have undergone several human-made improvements for cattle grazing, such as eliminating weeds and replanting of seeds adapted for grazing. Well-managed pastureland is environment-friendly because it allows the pasture to grow more rapidly, in a process that captures CO_2 from the air due to plant growth. In addition, when animals graze appropri-

[13] In Portuguese, the ABC program's official name is *Plano setorial de mitigação e de adaptação às mudanças climáticas para a consolidação de uma economia de baixa emissão de carbono na agricultura.*

ately in a well-managed pasture, they eat plants that will subsequently grow again—thus capturing more CO2 in the process. They also leave feces and urine in the fields, reducing the need for fertilizers.[14] However, when well-managed pastureland is not intensively grazed by cattle, the above environment-friendly benefits do not occur.

Our data allow us to compute the percentage of farmers practicing no-till farming and the percentage of livestock producers with well-managed pastureland. Due to constraints on the availability of data, this additional analysis cannot be conducted using our preferred panel data model but instead with a cross-section specification.

Our findings suggest that the effect is driven by high-exposed municipalities adopting less environmentally-friendly management practices. Figure 5 depicts that no-till areas have decreased in high-exposed localities. Nevertheless, such municipalities have shown increases in areas for well-managed pastureland—however, with a lower number of heads per hectare as shown in Figure 4. This means well-managed pastureland does not present the environmental benefits they would if properly grazed. This is consistent with the fact that the ABC Plan puts emphasis precisely on financing such management practices.[15]

Conceptually, the results can be rationalized by producers facing a trade-off between the adoption of greener and credit-subsidized practices but whose adoption takes longer due to a learning process.[16] Strong economic incentives to expand production may increase the opportunity costs of the learning process. As a result, producers end up adopting non-green practices. Although given a greener and cheaper option for financing by the ABC program, this may explain why producers chose to take other types of credit instead.

The second exercise checks whether agricultural emissions have increased in the shorter panel period from 2013-2017. Interestingly, the results from Figure 5 show that net GHG emissions continue to present a similar pattern—i.e., increased in more exposed localities—as in the previous analysis with the more extended panel.

4.5 Further Results

This subsection aims to perform further analysis to check (i) how different biomes were affected by the boom and (ii) the relative importance of crops versus livestock in explaining the baseline results.

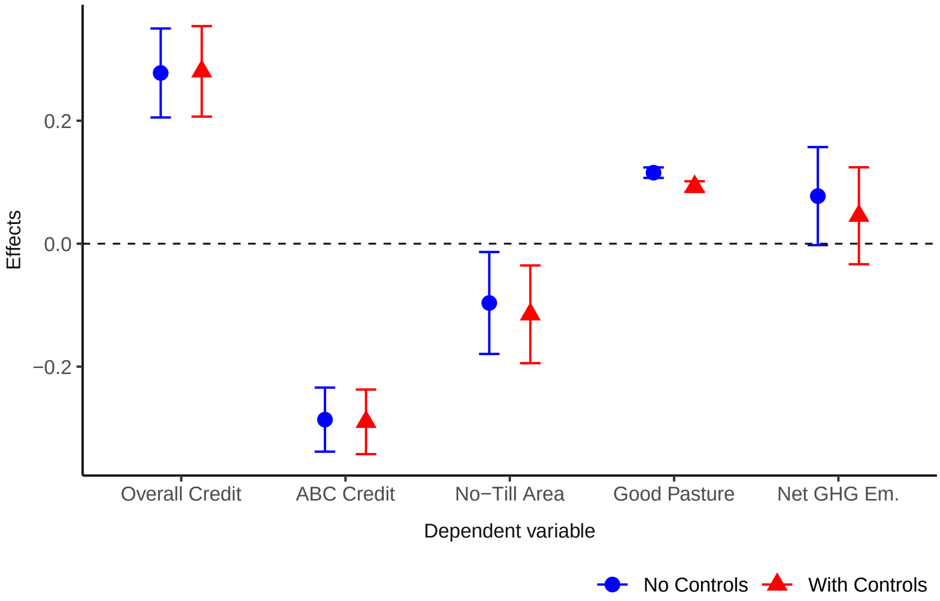
In the biomes analysis, we focus on Brazil's two most important biomes: the Amazon and the Cerrado. The results are presented in Figure 6 and suggest that both biomes experienced higher emissions, deforestation rates, and fires as a consequence of the commodity boom. In particular, notice that deforestation impacts have been more significant in the

[14] The specialized literature indicates that under a high-intensity, well-managed pasture, it is possible to produce beef cattle while sequestering CO2 from the atmosphere due to plant growth (e.g., Oliveira et al. (2020)). Torres et al. (2017) show similar results for integrated systems, a tropical-agriculture technique according to which a farmer grows a commercial forest, a cash crop (spring-summer), and pasture (fall-winter) in the same area to maximize yield.

[15] Analyzing the legislation, we did not find that the bureaucratic process is different for the ABC credit compared to other credit types. Therefore, we can rule out the influence of bureaucracy as a mechanism.

[16] Brazilian Census data show that management practices toward no-till and well-managed pastureland are not widespread but have been expanding over the last years.

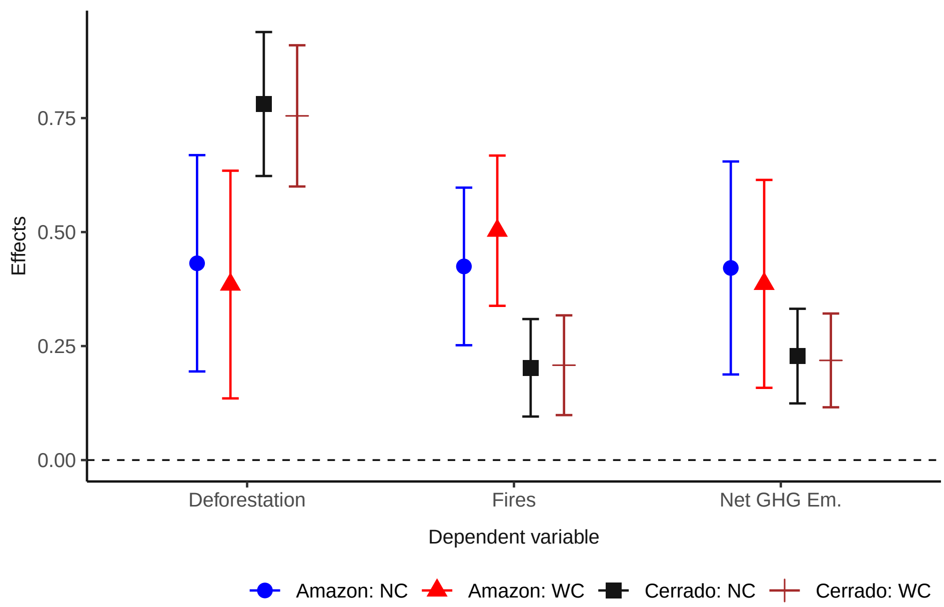
Figure 5: Effects of Commodity Booms: Compliance with a Climate Mitigation Policy



Notes. This figure presents the results from the estimation of Equation (1) for five dependent variables: Overall Credit, ABC Credit, No-Till Area, Good Pasture Area, and Net GHG Emissions. The unit of observation is municipality-year for Overall Credit, ABC Credit, and Net GHG Emissions for years 2013 to 2017. We also run a cross-section version of Equation (1) for year 2017 for No-Till Area and Good Pasture Area. Net GHG emissions are measured in tons of CO2eq., and Overall Credit and ABC Credit values are in 2010 *reais*. No-Till Area and Good Pasture Area are measured in hectares. Dependent variables and the commodity exposure index are transformed into $log+1$—see Appendix Table A.21 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

Cerrado than in the Amazon. A 1% increase in exposure to the commodity cycle is associated with 0.75% more deforestation in the Cerrado. The opposite is observed for the number of fires: impacts are more significant in the Amazon, where a 1% increase in exposure results in 0.50% more fires. Notice that fires do not occur naturally in the Amazon. Both biomes presented an increase in net GHG emissions, though the effects are larger in the Amazon. Therefore, these results indicate that the dynamics of the impacts of commodity booms on environmental variables—particularly deforestation and fires—are different for distinct biomes. This relates to descriptive data of our period of analysis showing that agriculture expansion in the Cerrado is more related to increases in the area for crops, while in the Amazon, it is more associated with the development of cattle raising.

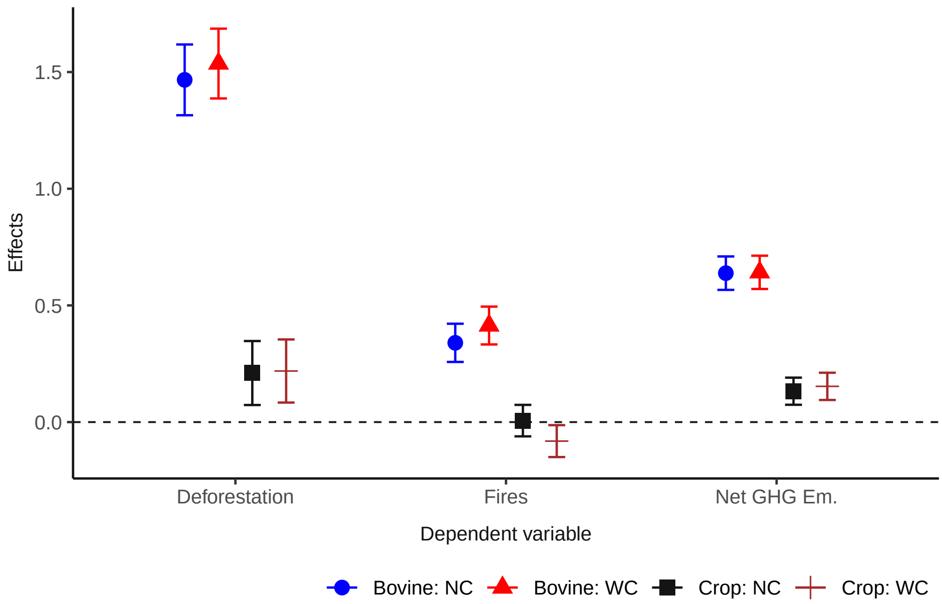
Figure 6: Effects of Commodity Booms: Cerrado and Amazon Biomes



Notes. This figure presents the results from the estimation of Equation (1) for three dependent variables: Deforestation, Number of Fires, and Net GHG Emissions for Cerrado and Amazon municipalities from 2001-2017. The unit of observation is municipality-year. The change in yearly deforestation is measured in squared kilometers, and the number of fires is the yearly count. Net GHG Emissions are the CO2eq. in tons per year. Dependent variables and the commodity exposure index are transformed into $log+1$—see Appendix Table A.22 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall). NC stands for "No Controls" and WC stands for "With Controls".

Crops and cattle raising may have contributed differently to the environmental impacts we observe. To analyze the disaggregated effects, we split the commodity exposure index of Equation (2)into two indices: livestock exposure index and crops-only exposure index. We find that municipalities presented a higher response to deforestation, fires, and net GHG emissions given exposure to beef exposure—notice that in Figure 7 the coefficients from “Bovine" are greater in magnitude than “Crop". Furthermore, we find that commodity booms given by crop prices are more related to deforestation than fires. Collectively, these results suggest that the effects we observe are driven by the livestock sector. The results from cattle raising exposure relate with the increasing area allocated to livestock and the extensive livestock production we observe (recall Figure 3).

Figure 7: Effects of Commodity Booms: Livestock and Crops



Notes. This figure presents the results from the estimation of Equation (1) for three dependent variables: Deforestation, Number of Fires, and Net GHG Emissions for Brazilian municipalities from 2001 to 2017. We analyze the effects estimating Equation (2) and splitting the commodity exposure index into livestock index and crops only index (“Bovine" and “Crop", respectively). The unit of observation is municipality-year. The change in yearly deforestation is measured in squared kilometers, and the number of fires is the yearly count. Net GHG Emissions are the CO2eq. in tons per year. Dependent variables and the commodity exposure index are transformed into $log+1$—see Appendix Table A.23 for the results with the hyperbolic inverse sine transformation. Standard errors are clustered at the municipal level. We show 95% confidence intervals above. Controls include demographic variables (population size, unemployment rate, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall). NC stands for “No Controls" and WC stands for “With Controls".

4.6 Robustness and Specification Checks

We perform several robustness exercises and specification tests. Below, we detail each exercise and show that our findings are largely robust. In the interest of space, we only report tables of the robustness exercises in the online Appendix A. We focus on four dependent variables: deforestation, fires, net GHG emissions, and ABC credit.

Alternative Commodity Exposure Indices. We start by using the two alternative definitions of commodity exposure. The results displayed in Appendix Tables A.3 and A.4 support the claim that deforestation, fires, net GHG emissions, and ABC credit are robust to these alternative measures.

Inference. We also tested whether the results are robust to alternative clustering of the standard errors. We perform an inference assessment proposed by Adão et al. (2019) to account for possible cross-regional correlation in the error terms. Appendix Table A.5 shows that the significance of the results holds after applying the inference correction. We also performed an inference assessment by Ferman (2021), shown in Appendix Table A.6, which further alleviates concerns of the clustering at the municipal level. Moreover, in Appendix Table A.7 we cluster the standard errors into micro-regions and meso-regions. Micro-regions are sets of contiguous municipalities that share a common local labor market, while meso-regions are sets of contiguous micro-regions. Once more, the significance of results is highly robust.

Multiple Hypothesis Testing. We use Holm (1979)'s family-wise error rates correction to adjust the p-values of individual tests as a function of the number of tests (outcomes). The intuition of the correction is the following. Let α be the level of statistical significance and S be the number of outcomes within a "family". We consider outcomes within each Subsection 4.1–4.4 as a separate "family" (e.g., outcomes in Subsection 4.1 are considered one family of outcomes; and outcomes in Subsection 4.2 are considered another family). Within each family, the most significant hypothesis has a corrected p-value of α/S, which equivalent to a Bonferroni correction. The second most significant has a corrected p-value equivalent to $\alpha/(S-1)$. Finally, the jth most significant hypothesis has a corrected p-value of $\alpha/(S-j+1)$. Appendix Table A.8 presents the multiple hypothesis testing exercise. The results strongly support the significance of our main results.

Pre-trends. We perform a pre-trends analysis using data from historical Agricultural Censuses. Satellite data in Brazil do not allow us to further back in time, so we leverage historical data. From the censuses of 1970, 1975, 1980, 1985, 1995, 2006, and 2017, we obtain data on "Natural Forested Area Inside Farm Establishments" and "Forest Reserves in Farms." Both variables are measured in hectares. Legislation in Brazil requires that farms must hold a share of their area in the form of forests. "Natural Forested Area" measures the area of natural forests inside farms. "Forest Reserves" measures the area covered by natural forests that exceed the law requirements. We estimate Equation (1) using these two variables as proxies for deforestation. Appendix Table A.9 presents the results. As expected, the commodity exposure in the 2000s has zero effects on deforestation in either 1985–1995 or 1970–1995 periods. To further support our findings, we regress "Forest Reserves in Farms" in 2006-2017 on the commodity exposure for the 2000s. Consistently with the baseline deforestation analysis, we show that the commodity exposure decreased forest reserves (i.e., increased deforestation).

As a second analysis to examine trends in related variables, we use deforestation data from MapBiomas (2021). We employ the natural forest cover change per year as a proxy for deforestation. The results are in Appendix Table A.9 and remain robust. Finally, Appendix Table A.10 uses the main data on deforestation, fires, and net GHG emissions and performs a sensitivity test for the period 2001–2004 when the commodity boom had not yet started with full intensity. Results are either not statistically insignificant or small in magnitude.

Other empirical specifications. In the Appendix Table A.11 we run a Poisson fixed effects regression to account for the fact that the number of fires is a count variable. Results are robust after estimating using that alternative model. We also run a first difference model in Appendix Table A.12. Our baseline results are also robust to this new empirical model.

Number of Commodities. We also check whether our results remain valid with a greater number of commodities. In particular, we add to our original nine commodities ten more: sheep, flows, cotton, groundnut, barley, tobacco, sorghum, wheat, latex, and Indian tea. In Appendix Table A.13 we display our results, which support our baseline results.

Brazil as Top Producer. Brazil is among top producers and exporters of several commodities (e.g., soybeans, maize, bovines). Hence, one might consider that some individual commodity could have their prices affected by production changes inside one or more of Brazil's municipalities. Thus, we perform a robustness check in which we exclude from our commodity index from Equation 1 one of our nine commodities at a time. Results are shown in Appendix Table A.14.

Placebo exercises. We perform three placebos exercises to check the validity of our results. The idea is to study cases in which commodity exposure should not affect environmental outcomes. We focus on three placebos where we restrict our sample of municipalities: highly-urbanized municipalities in non-agricultural areas, highly-urbanized municipalities in non-agricultural areas of Brazil's more developed state, and natural resources deposits (in which the production has a clear area delimitation and prices would not promote an area expansion). In Appendix Table A.15, we restrict municipalities with over 95% urbanization rates in more established states (SE, SP, SC, RJ, RS, RN, PE, PR, PB, MG, ES, CE, and BA) to show that those areas are not subject to deforestation, fires, or agricultural GHG emissions. In Appendix Table A.16, we restrict municipalities only from São Paulo state and results are small in magnitude and statistically insignificant. In Appendix Table A.17, we run a placebo with mineral production, using municipalities that collected a mining tax—CFEM—to proxy for the importance of such a sector in the municipality's economy. We then build the new commodity exposure index with data on iron ore prices, the most widespread mining commodity in Brazil. International prices of iron ore have also increased steeply during our analysis period. The extent to which mineral production impacts environmental outcomes should be different: agricultural production is diffused throughout the country, whereas mineral production is concentrated in pockets. Reassuringly, our findings are near zero in magnitude and statistically insignificant for deforestation, the number of fires, net GHG emissions, and ABC credit.

Transformations of the dependent variable. Recall that the baseline results use the log transformation for the dependent variable and the commodity exposure index. We investigate and find that the results are robust for using the hyperbolic inverse sine transformation—see Appendix Tables A.18–A.23. We also test for different log specifications in Table A.24. First, we assign the $log(y)$ transformation for variable values greater than 1, and use $log(y+1)$ for variable values between 0 and 1; we then create a dummy variable equal to 1 for the latter, and utilize it as control in running Equation (1). Subsequently, we perform a similar exercise, but instead of using $log(y+1)$ transformation for values between 0 and 1, we assign y itself; after that, we create the same dummy variable for control in running Equation (1). We also test dummies accounting for dependent variables greater than 0 in the main specification. The results are largely robust.

Alternative definitions of spatial units. Furthermore, we perform an exercise using micro-regions, the spatial units that are more related to the concept of local labor markets. The Brazilian Bureau of Statistics defines micro-regions, and there are 510 units in our period of analysis. Since micro-regions are more aggregated spatial units, this exercise aims to control for spillovers to neighboring municipalities, which may be experiencing pressures from the expansion of economic activities. Table A.25 reports, however, that results are robust when using the definition of micro-regions. We also carry out an exercise with Minimum Comparable Areas (MCAs), which are sets of municipalities whose borders were constant over the study period. Historically, Brazil has undergone the process of detachments and splits of municipalities. In 1940 there were 1,574 municipalities, while in 2000 there were 5,507 (Cavalcanti et al., 2019). From 2001–2017, there were approximately 50 newly created municipalities. We show in Table A.26 that results are unchanged when using the concept of MCAs.

Scaling up the dependent variables. Finally, we divide our dependent variables by (i) the population size in 2000, (ii) the number rural establishments in 1995, and (ii) the area in 1995 in hectares—see Tables A.27, A.28, and A.29, respectively. The results are again largely robust.

5 Conclusion

In this paper, we study how commodity booms affect the primary driver of climate change: greenhouse gas emissions. Commodity booms are associated with *carbonizing* factors (as measured by deforestation and fires) as well as *decarbonizing* factors (for instance, allocation of land toward lower-emission crop mix and higher crop productivity). It is, thus, ex-ante unclear whether commodity booms generate an increase in net GHG emissions. Taking into consideration carbonizing and decarbonizing factors, we show that Brazilian localities more exposed to commodity booms present an increase in net GHG emissions. Our findings highlight that market forces can promote GHG mitigation (“market-driven mitigation"), but one needs to consider several pathways to assess how economic growth affects net emissions.

Curbing GHG emissions is deemed to be essential to slow climate change. In particular, managing greenhouse gas emissions is key to reach the Paris Agreement’s goal of limiting the increase in global temperature. Our findings on the carbon footprint of commodity booms have relevant implications. Carbonizing factors such as deforestation and fires can have adverse impacts by interfering with infant, children, and adult health (e.g., Reddington et al., 2015; Rangel & Vogl, 2019; Zivin, Liu, Song, Tang, & Zhang, 2019). They can also impact the world at large because of externalities that spread beyond countries’ borders, aggravating climate-exacerbated hazards.

We also document a novel fact about economic booms by providing evidence on the extent to which they influence climate mitigation policies. We show that the take-up of ABC credit promoting sustainable agricultural practices was lower in localities more exposed to commodity booms. A policy-relevant implication is that—as countries transition to net-zero emissions of greenhouse gases—voluntary compliance to mitigation policy is affected by macroeconomic conditions and may need strong incentives to achieve the targeted goals.

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Appendix A Additional Figures and Tables

Table A.1: Summary Statistics

Statistic	Unit	N	Mean	St. Dev.	Min	Max
Real Agricultural GDP	millions BRL	87,936	36,818.3	81,276.6	6.2	2,585,893
Yearly Deforestation	square Km	28,375	17.9	53.7	0.0	1,808.6
Number of Fires	count	74,511	54.3	207.1	1.0	13,079.0
GHG Emissions	tons of CO2e	90,594	352,906.9	1,385,339.0	−1,062,874.0	100,047,782.0
Agriculture GHG Emissions	tons of CO2e	90,563	92,464.2	179,930.5	0.0	4,227,780.0
Land-use GHG Emissions	tons of CO2e	90,579	193,705.3	1,237,096.0	0.0	97,402,501.0
Net GHG Emissions	tons of CO2e	90,579	263,813.9	1,313,016.0	−15,574,611.0	93,873,248.0
Real ABC Credit	BRL	27,024	304,957.3	1,271,038.0	0.0	88,123,692.0
Real Overall Credit	BRL	27,024	2,553,277.0	5,664,685.0	0.0	170,694,782.0
Total Area	hectares	10,004	96,369.2	215,637.4	109	8,696,146
Pasture Land	hectares	10,174	30,283.4	80,502.5	0.0	3,695,164.0
Crop Land	hectares	10,171	10,792.5	34,495.1	0.0	1,155,466.0
No-Tillage Area	hectares	10,167	4,643.3	20,191.9	0.0	547,878.0
Population	count	93,432	1,137.1	37,921.5	0.0	10,435,546.0
Municipality Area	square Km	93,432	1,524.9	5,626.1	3.6	159,533.3
Average Rain	milimiters	92,769	1,394.1	508.8	201.2	4,043.5
Average Temperature	degrees Celsius	92,769	22.9	3.0	13.7	31.0
Unemp. Rate (2001)	percentage	93,432	0.6	2.6	0.0	56.0
Illit. Rate (2001)	percentage	93,432	1.4	6.4	0.0	63.0
Povert. Rate (2001)	percentage	93,432	2.4	11.1	0.0	90.8
Number of Tractors	count	9,546	204.6	304.7	3.0	4,646.0
CE 1 (BRL)	instrument	93,432	6.2	18.2	0.0	851.5
CE 2 (BRL)	instrument	93,194	10.6	25.9	0.0	769.2
CE 3 (BRL)	instrument	82,410	17.5	6.5	9.2	34.1

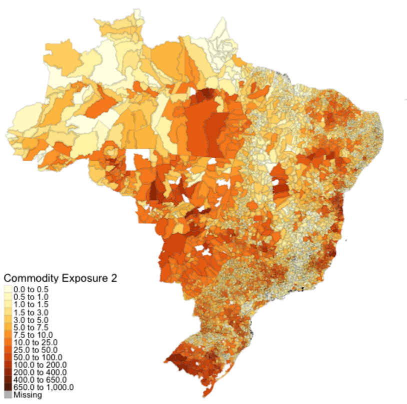
Notes. This table presents the descriptive statistics of all relevant variables taken into account in the estimations performed in this paper. Observations range from 2001 to 2017. All monetary values have been deflated by the Brazilian Consumer Price Index (IPCA) calculated by IBGE and are denominated in 2010 *reais*. Notice that "GHG Emissions", "Net GHG Emissions", and "Net Emissions land-use" have negative minimum values because SEEG estimates the sequestration of greenhouse gas gases for Brazilian municipalities, and a few of them are able to sequester more carbon than they release, which is mathematically represented with negative values.

Table A.2: Agricultural Products by Producing Municipalities

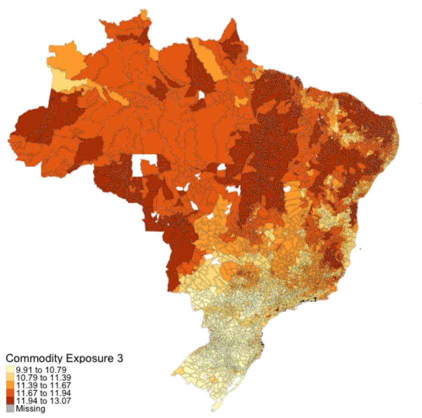
Produce	Number of Municipalities	Percent Change # Municipalities	Percent Change Prices in USD
Bovines	5,471	+17.1%	+52.9%
Maize	5,259	+ 12.7%	+17.2%
Banana	3,873	+12.2%	+46.8%
Sugar	3,878	+4.0%	+0.001%
Rice	3,340	-38.7%	+20.9%
Orange	3,320	-7.3%	-9.5%
Soy	2,328	+37.0%	+35.3%
Coffee	1,904	-11.5%	+21.7%
Cocoa	318	+22.2%	+17.8%

Notes. This table presents the number of municipalities which have produced each of the agricultural products described in the column "Produce" for at least one year in 2006 or 2017 and the percent change in the number of producing municipalities in the same period.

Figure A.1: Alternative Commodity Exposure Indexes



(a) Commodity Exposure 2



(b) Commodity Exposure 3

Table A.3: Using Commodity Exposure 2

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.780***	0.803***	0.470***	0.498***	0.152***	0.153***	−3.201***	−3.276***
	(0.067)	(0.067)	(0.028)	(0.028)	(0.028)	(0.028)	(0.445)	(0.445)
Panel B (asinh)								
Commodity Exposure	0.533***	0.560***	0.428***	0.453***	−0.345***	−0.312**	−2.976***	−3.099***
	(0.058)	(0.070)	(0.029)	(0.030)	(0.134)	(0.127)	(0.429)	(0.429)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,346	27,751	74,443	73,816	90,387	89,743	27,004	26,835
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). We use the commodity exposure index from Equation (4) calculated with shares 1996-2000 for years 2001-2017 and with shares 2008-2012 for years 2012-2013. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.4: Using Commodity Exposure 3

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	6.409***	6.893***	3.354***	3.052***	2.008***	2.080***	27.144***	32.141***
	(0.653)	(0.659)	(0.353)	(0.360)	(0.278)	(0.282)	(5.904)	(9.359)
Panel B (asinh)								
Commodity Exposure	6.507***	7.110***	3.667***	3.008***	7.316***	6.193***	26.883***	30.340***
	(0.736)	(0.746)	(0.383)	(0.391)	(1.267)	(1.178)	(6.093)	(9.734)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,366	24,841	65,880	65,327	79,562	78,994	16,260	16,152
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). We use the commodity exposure index from Equation (5) calculated with shares 1996-2000 for years 2001-2017 and with shares 2008-2012 for years 2012-2013. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.5: Inference Assessment By Adão et al. (2019)

Dependent Variable	Commodity Exposure	Method	St. Errors	p-value	Lower Ci	Upper CI
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Deforestation	0.2175079 (n.obs: 170)	*EHW*	0.10375147	0.0360439025	0.01415874	0.4208570
		AKM	0.05922042	0.0002398574	0.10143801	0.3335778
		AKM0	0.07844406	0.0161788639	0.07299010	0.3804852
Number of Fires	0.2784382 (n.obs: 801)	*EHW*	0.03286320	0.0000000000	0.2140275	0.3428489
		AKM	0.04450608	0.0000394516	0.1912078	0.3656685
		AKM0	0.06581025	0.0262878000	0.0764480	0.3344195
Net GHG Emissions	0.24077000 (n.obs: 2,201)	*EHW*	0.03176943	3.486100e-14	0.17850170	0.3030356
		AKM	0.08289275	3.677461e-03	0.07830183	0.4032355
		AKM0	0.14393643	1.375192e-01	-0.22271765	0.3415028

Notes. This table presents the results of the assessment proposed by Adão et al. (2019). We run a first difference specification of Equation (1) for years 2006 and 2017 without any controls to assess the robustness of our results due to the possibility of correlation among the shares of localities not necessarily close to each other. We use a log transformation for the dependent variable and the commodity exposure index. In column (i) we present the estimated coefficient and the number of observations for each regression (n. obs) in parenthesis for each dependent variable in the leftmost column. In column (iii) we specify the methods employed in estimating the standard errors. "EHW" stands for Eicker-Huber-White standard errors, while "AKM" stands for the method proposed by Adão-Kolesár-Morales and "AKM0" with null imposed (the reported standard error for this method corresponds to the normalized standard error, given by the length of the confidence interval divided by $2z_{1-\alpha/2}$). We used the "ShiftShareSE" package in R to estimate these results.

Table A.6: Inference Assessment by Ferman (2021)

Dependent Variable	Commodity Exposure	Assessment (5% test)
	(i)	(ii)
Deforestation	0.891	0.0537
Number of Fires	0.2422	0.0537
Net GHG Emissions	0.9122	0.0575
ABC Credit	-0.4279	0.0625

Notes. This table presents the results of the assessment proposed by Ferman (2021). We run a first difference specification of Equation (1) for years 2003 and 2013 with controls to assess the robustness of our results due to the possibility of under- and over-rejection. We use the $log+1$ transformation for the dependent variable and the commodity exposure index. In column (i) we present the estimated coefficients for each first difference regression with dependent variable described in the left-most column. For regressions with dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" we use the commodity exposure index calculated with shares from 1996-2000. For regression with dependent variable "ABC Credit" we utilize the commodity exposure index calculated with shares from 2008-2012. In column (ii) we show the assessment-5%-test results while holding **X** constant—as in $y = X\beta + \varepsilon$. For 800 simulations, the assessment yields the percentage of times the null would be rejected. Our results remain largely significant. We use Ferman's code in Stata to run this assessment.

Table A.7: Standard Errors Clustered at Micro- and Meso-Regions

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.617	0.620	0.154	0.124	0.240	0.247	-3.19	-3.39
	(0.125)***	(0.121)***	(0.056)***	(0.0578)**	(0.0516)***	(0.0511)***	(0.519)***	(0.521)***
	[0.165]***	[0.161]***	[0.0872]*	[0.0901]	[0.0516]***	[0.0511]***	[0.604]***	[0.616]***
Panel B (asinh)								
Commodity Exposure	0.463	0.466	0.139	0.100	0.104	0.089	-2.73	-2.93
	(0.114)***	(0.111)***	(0.0498)***	(0.0514)*	(0.159)	(0.149)	(0.471)***	(0.475)***
	[0.137]***	[0.137]***	[0.0742]*	[0.0767]	[0.189]	[0.176]	[0.552]***	[0.561]***
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,346	27,751	74,443	73,816	90,387	89,743	27,024	26,853
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the micro-region level in parenthesis (above) and at the meso-region level in brackets [below]. We follow IBGE's definition for micro and meso-regions. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Multiple Hypothesis Testing Correction

Description	Dependent Variable	Coefficient	P-Value	Multiple Hypothesis Test — Corrected P-Value
	(i)	(ii)	(iii)	(iv)
Figure 2	Agricultural GDP	0.294***	0.0000000000	0.0000000000
	Pasture and Crop Land	0.611***	0.0000000058	0.0000000464
	Deforestation	0.620***	0.0000000000	0.0000000000
	Number of Fires	0.124***	0.0001096468	0.0013157620
Figure 3	% Pasture	0.139***	0.0000000174	0.0000000156
	Heads/Hectare	-0.229***	0.0000019650	0.0000216150
	Crop/Hectare	0.077*	0.0049288180	0.0640746300
	Tractors/Hectare	0.433***	0.0000000000	0.0000000000
	% Lower Em. Crops	0.403***	0.0000000000	0.0000000000
Figure 4	Gross GHG Emissions	0.270***	0.0000000000	0.0000000000
	Agric. GHG Emissions	0.113***	0.00000077720	0.0000077720
	Land-Use GHG Emissions	0.249***	0.0000000001	0.0000000007
	Net GHG Emissions	0.247***	0.0000000000	0.0000000000
Figure 5	Overall Credit	0.216***	0.0000000042	0.0000000126
	ABC Credit	-0.239***	0.0000000000	0.0000000000
	No-Till Area	-0.149	0.0578300000	0.2313200000
	Well-Managed Pastureland	-0.077***	0.0000000000	0.0000000000
	Net GHG Emissions	0.063	0.1626030000	0.813015000

Notes. This table presents the results of multiple hypothesis testing following Holm (1979), as described in Subsection 4.6. We consider outcomes within each Subsection 4.1-4.4 as a separate "family" (e.g., outcomes in Subsection 4.1 are considered one family of outcomes; and outcomes in Subsection 4.2 are considered another family). Within each family, the most significant hypothesis has a corrected p-value of α/S, which equivalent to a Bonferroni correction. The second most significant has a corrected p-value equivalent to $\alpha/(S-1)$. Finally, the jth most significant hypothesis has a corrected p-value of $\alpha/(S-j+1)$. Hence, for each of our main results in Figures 2 through 4 described in the left-most column above, we perform this procedure—which yields a new multiple-hypothesis-p-value presented in column (iv). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Pre-Trends for Deforestation - With Agricultural Census and MapBiomas Data

	Dependent variable:									
	Excess Forest Reserves in Farms (log)		Natural Forested Areas Inside Farms in Hectares (log)				Deforestation of Natural Forests from MapBiomas (log)			
	Verifying whether it is a good proxy 2006-2017		*Pre-Trends* 1985 - 1995 (2006-2017)		*Pre-Trends* 1970-1975-1980-1985-1995 (2001-2005-2009-2013-2017)		Verifying whether it is a good proxy 2002-2017		*Pre-Trends* 1985 to 2000 (2002 to 2017)	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Panel A (log)										
Commodity Exposure	-2.999^{***}	-0.487^{**}	0.004	-0.180	0.040	-0.009	0.765^{***}	0.744^{***}	-0.038	-0.043
	(0.195)	(0.199)	(0.117)	(0.133)	(0.077)	(0.076)	(0.076)	(0.076)	(0.075)	(0.075)
Panel B (asinh)										
Commodity Exposure	-2.794^{***}	-0.506^{***}	0.043	-0.136	0.029	-0.002	1.722^{***}	1.666^{***}	-2.515^{***}	-2.856^{***}
	(0.176)	(0.184)	(0.109)	(0.125)	(0.071)	(0.071)	(0.243)	(0.244)	(0.268)	(0.268)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,867	9,794	9,051	8,998	20,913	20,818	46,820	46,498	45,843	45,565
Estimation	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Excess Forest Reserves in Farms", "Natural Forested Area Inside Farm Establishments", and "Deforestation of Natural Forests", which are all measured in hectares. The former variable measures the area inside farms which are covered by natural forests exceeding the requirements of Brazilian law. The middle variable measures the area of natural forests inside farms, for a period which Brazilian environmental law was overseen. Both data are sourced from the Agricultural Censuses of 1970, 1975, 1980, 1985, 1995, 2006, and 2017. We use both variables as proxies for deforestation. The latter variable is the first difference from MapBiomas' database on Natural Forests by municipality—we take the first difference of this variable to capture the change in forested area, which gives us a good proxy for deforestation in hectares. In columns (iii) through (vi) and (ix) and (x), we present the years employed in the pre-trends analysis: years above correspond to the original data period and years below in parenthesis correspond to the assigned period in our dataset. In Panel A, the dependent variable and the commodity exposure index are transformed into $log+1$. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.10: Sensitivity Test - 2001 to 2004

	Dependent variable:					
	Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure	0.552^{**}	0.239	0.271^{**}	0.072	-0.029	-0.058
	(0.216)	(0.202)	(0.107)	(0.104)	(0.060)	(0.062)
Panel B (asinh)						
Commodity Exposure	0.496^{**}	0.229	0.295^{***}	0.019	-0.100	-0.240
	(0.229)	(0.218)	(0.109)	(0.107)	(0.252)	(0.253)
Initial Controls	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,823	6,683	17,665	17,516	19,416	19,334
Estimation	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables “Deforestation", “Number of Fires", and “Net GHG Emissions" from 2001-2004 for Brazilian municipalities. The purpose is to test our results for a period when commodity prices were relatively stable, which was followed by the super-cycle. In Panel A, the dependent variables and the commodity exposure index are transformed into $log+1$. In Panel B, variables are transformed using $asinh$ (the hyperbolic inverse sine). The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.11: Poisson Estimates for the Number of Fires

	Dependent variable:	
	Number of Fires	
	(i)	(ii)
Panel A (log)		
Commodity Exposure	0.0340**	0.0211*
	(0.0122)	(0.0125)
Panel B (asinh)		
Commodity Exposure	0.0312**	0.0166
	(0.010)	(0.0102)
Initial Controls	No	Yes
Weather Controls	No	Yes
Municipality	Yes	Yes
Observations	74,511	73,884
Estimation	Poisson	Poisson

Notes. This table presents results from estimation of a Poisson version of Equation (1) for dependent variable "Number of Fires" from 2001-2017. The number of fires is the actual count of fires per municipality. In Panel A, the dependent variables and the commodity exposure index are transformed into $log+1$. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Taking the First Difference - Δ(2003-2013)

	Dependent variable:					
	Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure	0.963^{***}	0.842^{***}	0.120	0.380^{***}	0.671^{***}	0.646^{***}
	(0.167)	(0.185)	(0.088)	(0.091)	(0.066)	(0.066)
Panel B (asinh)						
Commodity Exposure	0.661^{***}	0.464^{**}	0.102	0.306^{***}	0.685^{**}	0.539
	(0.193)	(0.211)	(0.092)	(0.094)	(0.343)	(0.339)
Initial Controls	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,437	3,367	8,962	8,886	10,967	10,889
Estimation	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (3) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" for Brazilian municipalities in 2003 and 2013. The dependent variables and the commodity exposure index are transformed into $log+1$. In Panel B, variables are transformed using $asinh$ (the hyperbolic inverse sine). The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (5). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.13: Using More Commodities

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.378^{***}	0.378^{***}	0.306^{***}	0.308^{***}	0.024	0.024	-2.614^{***}	-2.428^{***}
	(0.066)	(0.066)	(0.028)	(0.028)	(0.026)	(0.027)	(0.453)	(0.452)
Panel B (asinh)								
Commodity Exposure		0.210^{***}	0.202^{***}	0.282^{***}	0.282^{***}	-0.477^{***}	-0.444^{***}	-2.042^{***}
-2.165^{***}								
	(0.068)	(0.068)	(0.030)	(0.030)	(0.131)	(0.128)	(0.445)	(0.447)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (Panel A)	28,623	28,028	74,511	73,884	89,688	89,407	27,024	26,853
Observations (Panel B)	28,623	28,028	74,511	73,884	93,415	92,769	27,024	26,853
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2001-2017 for Brazilian municipalities. We use an expanded exposure commodity index from Equation 2 which include the following commodities: bovines, orange, coffee, banana, cocoa, soybeans, maize, sugarcane, rice, sheep, flows, cotton, groundnut, barley, tobacco, sorghum, wheat, latex, and Indian tea. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Removing One Commodity at a Time

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel 1								
Commodity Exposure - without soybeans	0.606***	0.605***	0.149***	0.137***	0.256***	0.257***	−3.135***	−3.337***
	(0.067)	(0.067)	(0.032)	(0.032)	(0.028)	(0.028)	(0.426)	(0.430)
Panel 2								
Commodity Exposure - without maize	0.619***	0.618***	0.145***	0.122***	0.248***	0.251***	−3.322***	−3.528***
	(0.067)	(0.067)	(0.032)	(0.032)	(0.028)	(0.028)	(0.428)	(0.432)
Panel 3								
Commodity Exposure - without sugar	0.576***	0.567***	0.095***	0.068**	0.240***	0.243***	−3.236***	−3.435***
	(0.068)	(0.068)	(0.032)	(0.032)	(0.028)	(0.028)	(0.431)	(0.435)
Panel 4								
Commodity Exposure - without rice	0.618***	0.614***	0.149***	0.131***	0.261***	0.264***	−3.150***	−3.328***
	(0.067)	(0.067)	(0.031)	(0.032)	(0.028)	(0.028)	(0.426)	(0.430)
Panel 5								
Commodity Exposure - without banana	0.605***	0.616***	0.188***	0.157***	0.265***	0.272***	−4.050***	−4.235***
	(0.066)	(0.066)	(0.032)	(0.032)	(0.029)	(0.028)	(0.441)	(0.444)
Panel 6								
Commodity Exposure - without orange	0.979***	0.973***	0.299***	0.292***	0.345***	0.345***	−2.699***	−2.966***
	(0.064)	(0.064)	(0.032)	(0.032)	(0.026)	(0.026)	(0.434)	(0.440)
Panel 7								
Commodity Exposure - without coffee	0.629***	0.633***	0.148***	0.102***	0.284***	0.293***	−2.704***	−2.728***
	(0.070)	(0.069)	(0.033)	(0.033)	(0.030)	(0.030)	(0.471)	(0.471)
Panel 8								
Commodity Exposure - without cocoa	0.658***	0.653***	0.101***	0.077**	0.221***	0.224***	−3.560***	−3.681***
	(0.070)	(0.070)	(0.032)	(0.033)	(0.030)	(0.029)	(0.473)	(0.476)
Panel 9								
Commodity Exposure - without bovines	0.210***	0.219***	0.006	−0.081**	0.132***	0.153***	−2.770***	−2.930***
	(0.070)	(0.069)	(0.034)	(0.035)	(0.030)	(0.030)	(0.398)	(0.402)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,623	28,028	74,511	73,884	89,688	89,407	27,024	26,853
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2001-2017 for Brazilian municipalities. We use the commodity exposure index from Equation 2 but we remove one commodity for each of the Panel 1 through 9. In Panel 1, we calculate the commodity exposure index without soybeans; in Panel 2, we calculate it without maize; and so forth up to Panel 9. The dependent variables and the commodity exposure index are transformed into $log+1$. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.15: Placebo - More Established and Urbanized States

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.246	0.295	0.254^{**}	0.197^{*}	0.135	0.125	-3.492^{*}	-3.535^{*}
	(0.235)	(0.230)	(0.115)	(0.114)	(0.099)	(0.097)	(1.967)	(1.972)
Panel B (asinh)								
Commodity Exposure	0.207	0.252	0.282^{**}	0.217^{*}	-0.533	-0.544	-2.849	-2.908^{*}
	(0.236)	(0.232)	(0.118)	(0.116)	(0.497)	(0.497)	(1.740)	(1.750)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	700	700	2,920	2,920	3,191	3,191	1,073	1,071
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities which have more than 95% of urbanization rates and are located in the following states: SE, SP, SC, RJ, RS, RN, PE, PR, PB, MG, ES, CE, BA. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are also clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.16: Placebo - Sao Paulo State

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	-0.076	-0.089	-0.139^{**}	-0.135^{**}	0.016	0.021	-2.133	-2.061
	(0.068)	(0.067)	(0.066)	(0.066)	(0.055)	(0.055)	(1.305)	(1.311)
Panel B (asinh)								
Commodity Exposure	-0.093	-0.116	-0.122^{*}	-0.121^{*}	-0.547^{*}	-0.540^{*}	-1.569	-1.506
	(0.080)	(0.079)	(0.069)	(0.069)	(0.303)	(0.304)	(1.206)	(1.209)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,868	2,868	8,358	8,358	8,930	8,930	3,049	3,049
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities in the state of Sao Paulo. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are also clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.17: Placebo With Mining Data

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	-0.002	-0.0004	-0.029	0.095	-0.187^{***}	-0.193^{***}	-0.932	-1.098
	(0.088)	(0.088)	(0.063)	(0.063)	(0.070)	(0.070)	(0.935)	(0.946)
Panel B (asinh)								
Commodity Exposure	-0.006	-0.002	-0.049	0.063	0.133	0.143	-0.963	-1.106
	(0.089)	(0.089)	(0.059)	(0.059)	(0.257)	(0.258)	(0.830)	(0.837)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,710	5,593	16,078	15,961	18,548	18,518	7,259	7,217
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2005-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. We use a different measure for the commodity exposure index, given by Equation (2), but using a mining tax (CFEM) as proxy for mineral production shares. We use 2004 as base year for shares and 2005-2017 for iron ore international prices in Brazilian *reais* as shifts. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are also clustered at the municipality level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.18: Effects of Commodity Booms: Economic Activity, Deforestation, and Fires

	Dependent variable:							
	Agricultural GDP		Pasture and Crop Land		Deforestation		Number of Fires	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.2865***	0.2946***	0.8836***	0.6333***	0.6224***	0.6213***	0.1538***	0.1239***
	(0.0229)	(0.0228)	(0.0674)	(0.0675)	(0.0678)	(0.0675)	(0.0317)	(0.0320)
Panel B (asinh)								
Commodity Exposure	0.246***	0.252***	0.818***	0.582***	0.470***	0.468***	0.139***	0.100***
	(0.020)	(0.020)	(0.061)	(0.062)	(0.066)	(0.066)	(0.030)	(0.030)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (Panel A)	87,936	87,312	10,553	10,477	28,623	28,028	74,511	73,884
Observations (Panel B)	87,936	87,312	10,553	10,477	28,623	28,028	74,511	73,884
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables “Agricultural GDP", “Pasture and Crop Land", “Deforestation" and “Number of Fires" from 2001-2017. Variable “Agricultural GDP" is the value for gross domestic product of the agricultural sector at the local level measured in 2010 Brazilian *reais*, “Pasture and Crop Land" is the sum of degraded, well-managed, and natural pasture-lands and total cropland in hectares given in the agricultural censuses of 2006 and 2017, “Deforestation" is change in yearly deforestation measured in squared kilometers, while the number of fires is the actual count of fires per municipality. In Panel A, the dependent variables and the commodity exposure index are transformed into $log + 1$. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.19: Effects of Commodity Booms: Land Allocation, Crop Mix, and Productivity

	Dependent variable:				
	% Pasture Land	Heads Per Hectare	Crop Prod. Hectare	Tractors Per Hectare	% Lower Emission Crop Land
	(i)	(ii)	(iii)	(iv)	(v)
Panel A (log)					
Commodity Exposure	0.1390^{***}	-0.1822^{***}	0.3155^{***}	0.4344^{***}	0.4032^{***}
	(0.0236)	(0.0529)	(0.0578)	(0.0401)	(0.0361)
Panel B (asinh)					
Commodity Exposure	0.108^{***}	-0.212^{***}	0.341^{***}	0.502^{***}	0.347^{***}
	(0.021)	(0.063)	(0.053)	(0.045)	(0.032)
Initial Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes
Observations (Panel A)	10,812	10,914	75,142	10,914	10,702
Observations (Panel B)	10,812	10,914	75,142	10,914	10,702
Estimation	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for Brazilian municipalities using agricultural census data from years 2006 and 2017. Our commodity exposure index is log-transformed. Column (i) presents the change in allocation of land between crop production and livestock, measured as a percentage of farmland. Columns (ii), (iii), and (iv) present productivity measures, showing heads of cattle livestock per hectare, crop-productivity per hectare measured as tons of produce per hectare, and number of tractors per hectare, respectively. Column (v) presents within crop allocation, from crops which are considered Lower Emission (such as soybeans, maize, and orange) and Higher Emission (such as rice and sugar-cane), measured in percentage of total crop-land. In Panel A, the commodity exposure variable is transformed into $log+1$ and dependent variables from columns (ii) through (iv) are transformed as well. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.20: Effects of Commodity Booms: Greenhouse Gas Emissions

	Dependent variable:			
	GHG Emissions Whole Economy	GHG Emissions Agriculture	GHG Emissions land-use	Net GHG Emissions Whole Economy
	(i)	(ii)	(iii)	(iv)
Panel A (log)				
Commodity Exposure	0.2716***	0.1143***	0.2601***	0.2507***
	(0.0204)	(0.0238)	(0.0370)	(0.0282)
Panel B (asinh)				
Commodity Exposure	0.193***	0.090***	0.186***	0.095
	(0.058)	(0.023)	(0.032)	(0.118)
Initial Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes
Observations (Panel A)	92,687	92,735	92,769	89,407
Observations (Panel B)	92,769	92,735	92,769	92,769
Estimation	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for different versions of greenhouse gas emissions dependent variables. Columns (i) through (iv) represent respectively: GHG emissions for the whole economy (gross), GHG emissions of agriculture (gross), GHG emissions of change in land-use (gross), and net GHG emissions for the whole economy. In Panel A, we utilize the $log+1$ transformation for all dependent variables and for our commodity exposure index. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.21: Effects of Commodity Booms: Compliance with a Climate Mitigation Policy

	Dependent variable:							
	Overall Credit		ABC Credit		No-Till Area	Well-Managed Pastureland	Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.2777***	0.2803***	−0.2862***	−0.2898***	−0.1148***	0.0343***	0.0774*	0.0454
	(0.0369)	(0.0376)	(0.0266)	(0.0268)	(0.0405)	(0.0029)	(0.0407)	(0.0402)
Panel B (asinh)								
Commodity Exposure	0.246***	0.274***	−0.293***	−0.310***	−0.0958***	0.0295***	0.051	0.046
	(0.040)	(0.040)	(0.028)	(0.028)	(0.0335)	(0.0047)	(0.0024)	(0.240)
Initial Controls	No	Yes	No	Yes	Yes	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	Yes	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Observations (Panel A)	27,370	27,175	27,370	27,175	5,407	5,220	25,969	25,887
Observations (Panel B)	27,370	27,175	27,370	27,175	5,407	5,220	27,365	27,175
Estimation	FE	FE	FE	FE	OLS	OLS	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Overall Credit", "ABC Credit", and "Net GHG Emissions" from 2013-2017 for Brazilian municipalities. Columns (i) through (iv) are measured in thousands of 2010 *reais*, and columns (vii) and (viii) are measured in tons of CO2eq. Columns (v) and (vi) present a cross-section analysis of year 2017 in which we run a similar regression to Equation (1) but without the fixed effects for municipality and time. Both variables are presented in percentage points relative to total crop area and total pastureland. In Panel A, the dependent variables and the commodity exposure index are transformed into $log+1$, apart from columns (v) and (vi) in which we apply log directly. In Panel B, all variables are transformed using the hyperbolic inverse sine transformation. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the same controls for the OLS regressions in columns (v) and (vi). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.22: Effects of Commodity Booms: Cerrado and Amazon Biomes

	Dependent Variable											
	Cerrado						*Amazon*					
	Deforestation		Number of Fires		Net GHG Emissions		Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Panel A (log)												
Commodity Exposure	0.781***	0.755***	0.202***	0.208***	0.228***	0.219***	0.432***	0.385***	0.425***	0.503***	0.421***	0.386***
	(0.081)	(0.079)	(0.055)	(0.056)	(0.053)	(0.052)	(0.121)	(0.127)	(0.088)	(0.084)	(0.119)	(0.116)
Panel B (asinh)												
Commodity Exposure	0.632***	0.623***	0.187***	0.192***	−0.138	−0.153	0.163	0.096	0.190**	0.296***	1.277**	0.970*
	(0.077)	(0.076)	(0.053)	(0.054)	(0.181)	(0.183)	(0.120)	(0.127)	(0.078)	(0.074)	(0.597)	(0.538)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (Panel A)	20,192	20,192	22,455	22,455	23,318	23,318	9,263	8,668	9,180	8,585	7,491	7,261
Observations (Panel B)	20,192	20,192	22,455	22,455	24,055	24,055	9,263	8,668	9,180	8,585	9,265	8,670
Estimation	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 for municipalities located in the Cerrado and the Amazon biomes. The dependent variables and the commodity exposure index are transformed into $log+1$. In Panel B, all variables are transformed using the hyperbolic inverse sine. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index given by Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.23: Effects of Commodity Booms: Livestock and Crops

	Dependent variable:					
	Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure (beef)	1.536^{***}		0.414^{***}		0.642^{***}	
	(0.076)		(0.041)		(0.036)	
Commodity Exposure (crops)		0.219^{***}		-0.081^{**}		0.153^{***}
		(0.069)		(0.035)		(0.030)
Panel B (asinh)						
Commodity Exposure (beef)	1.188^{***}		0.284^{***}		0.154	
	(0.078)		(0.036)		(0.142)	
Commodity Exposure (crops)		0.243^{***}		-0.075^{**}		0.329^{**}
		(0.066)		(0.033)		(0.128)
Initial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations (Panel A)	28,028	28,028	73,884	73,884	89,407	89,407
Observations (Panel B)	28,028	28,028	73,884	73,884	92,769	92,769
Estimation	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" for Brazilian municipalities over 2001-2017. "Deforestation" is change in yearly deforestation measured in squared kilometers, while the "Number of Fires" is the actual count of fires per municipality, and "Net GHG emissions" is measured in tons of CO2eq. In Panel A, the dependent variables and the commodity exposure index are transformed into $log+1$. In Panel B, we utilize the hyperbolic inverse sine transformation, which has a similar interpretation to the log transformation. In both panels A and B we untangle the effects using the shift-share approach from Equation (2) first only for beef and second only for crops under "Commodity Exposure (beef)" and "Commodity Exposure (crops)", respectively. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01. In both panels A and B we untangle the effects using the shift-share approach from Equation (2) only for beef and only for crops under "Commodity Exposure (beef)" and "Commodity Exposure (crops)", respectively

Table A.24: Testing for Different Log Specifications

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A								
log(y) for y>1; log(y+1), for 0<y<1								
dummy = 1 for y<1								
Commodity Exposure	0.682***	0.689***	0.168***	0.140***	0.257***	0.259***	−0.380***	−0.408***
	(0.073)	(0.072)	(0.029)	(0.029)	(0.030)	(0.030)	(0.064)	(0.064)
Panel B								
log(y) for y>1; y, for 0<y<1								
dummy = 1 for y<1								
Commodity Exposure	0.686***	0.693***	0.160***	0.135***	0.257***	0.259***	−0.380***	−0.408***
	(0.072)	(0.072)	(0.028)	(0.028)	(0.030)	(0.030)	(0.064)	(0.064)
Panel C								
dummy= 1 for y>0								
Commodity Exposure	0.635***	0.638***	0.169***	0.142***	0.278***	0.273***	−0.380***	−0.408***
	(0.067)	(0.067)	(0.027)	(0.027)	(0.021)	(0.020)	(0.064)	(0.064)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,375	27,780	93,432	92,769	93,432	92,769	27,024	26,853
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. In Panel A we utilize the following variable transformation process: if dependent variable y is greater than 1, we utilize $log(y)$; if $0 < y < 1$, we use $log(y+1)$; we then create a dummy variable equal to 1 for y values between 0 and 1. In Panel B we use the following: if dependent variable y is greater than 1, we utilize $log(y)$; if $0 < y < 1$, we use y; we then create a dummy variable equal to 1 for y values between 0 and 1. In Panel C we run our main specification with $log+1$ in both the dependent and exposure variables, but add dummies when our dependent variables are greater than 0. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.25: Using Micro-Regions To Account for Spillovers

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.242***	0.232***	0.164**	0.047	−0.329**	−0.398***	−2.699***	−2.424***
	(0.084)	(0.084)	(0.073)	(0.073)	(0.128)	(0.136)	(0.549)	(0.554)
Panel B (asinh)								
Commodity Exposure	0.164*	0.150*	0.143**	0.023	0.609	0.555	−2.604***	−2.364***
	(0.086)	(0.085)	(0.073)	(0.073)	(0.370)	(0.373)	(0.529)	(0.537)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,670	8,670	8,670	8,670	8,297	8,297	8,670	8,670
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and $asinh$ in Panel B. The unit of observation is micro-region-year. We use IBGE's definition of micro-region, with 510 units in our case. Standard errors are also clustered at the micro-region level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (2). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.26: Using MCAs — Minimum Comparable Areas

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.548***	0.554***	0.134***	0.104***	0.216***	0.220***	−3.245***	−3.509***
	(0.076)	(0.074)	(0.035)	(0.036)	(0.031)	(0.031)	(0.479)	(0.484)
Panel B (asinh)								
Commodity Exposure	0.425***	0.433***	0.131***	0.095***	0.121	0.112	−2.770***	−3.056***
	(0.074)	(0.073)	(0.034)	(0.034)	(0.137)	(0.134)	(0.441)	(0.447)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,898	19,626	57,107	56,803	67,250	67,134	20,896	20,805
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 using AMCs — "Áreas Minimamente Comparáveis" — instead of municipalities. The dependent variables and the commodity exposure index are transformed into $log+1$ in Panel A and using $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (5). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.27: Using Dependent Variables At Per Capita Level

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.002***	0.002***	0.003***	0.003***	36.368***	36.879***	−48.669***	−50.385***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(4.492)	(4.486)	(9.952)	(10.250)
Panel B (asinh)								
Commodity Exposure	0.001***	0.001***	0.001***	0.001***	22.051***	21.936***	−34.487***	−36.299***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(3.251)	(3.247)	(7.674)	(7.892)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,375	27,780	74,511	73,884	90,594	89,935	27,024	26,853
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2001-2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables are computed at the per capita level — square kilometers, number of fires, net GHG emissions, and ABC Credit are divided by the estimated population of municipalities—following IBGE's data. The commodity exposure index are transformed into $log+1$ in Panel A and using $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (5). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.28: Using Dependent Variables At Per Hectare

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	−0.002	−0.001	0.005	0.006*	−18.324	20.543	−311.090**	−318.979**
	(0.003)	(0.003)	(0.003)	(0.003)	(120.338)	(128.649)	(135.459)	(136.772)
Panel B (asinh)								
Commodity Exposure	0.00003	−0.001	0.005**	−0.009*	−33.367	95.020	−236.516**	−245.249**
	(0.0001)	(0.001)	(0.002)	(0.005)	(105.942)	(179.606)	(110.018)	(111.049)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,185	3,118	8,770	8,699	10,004	9,932	24,375	24,215
Estimation	FE	FE	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2006 and 2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables are computed at the per hectare level—square kilometers, number of fires, net GHG emissions, and ABC Credit are divided by the number of hectares used for crops and pastures in municipalities—following IBGE's data. The commodity exposure index are transformed into $log+1$ in Panel A and using $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (5). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.29: Using Dependent Variables At Per Establishment Level

	Dependent variable:					
	Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure	−0.033***	−0.033***	0.004	0.014	−620.679	−350.451
	(0.011)	(0.011)	(0.028)	(0.031)	(418.039)	(718.170)
Panel B (asinh)						
Commodity Exposure	−0.029***	−0.029***	0.007	0.016	−760.664**	−403.296
	(0.010)	(0.010)	(0.025)	(0.028)	(357.809)	(648.284)
Initial Controls	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,222	3,152	8,887	8,813	10,167	10,091
Estimation	FE	FE	FE	FE	FE	FE

Notes. This table presents results from estimation of Equation (1) for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions" from 2006 and 2017 and "ABC Credit" from 2013-2017 for Brazilian municipalities. The dependent variables are computed at the per establishment level — square kilometers, number of fires, net GHG emissions, and ABC Credit are divided by the number of rural establishments in municipalities—following IBGE's data. The commodity exposure index are transformed into $log+1$ in Panel A and using $asinh$ in Panel B. The unit of observation is municipality-year. Standard errors are clustered at the municipal level. Initial controls have time-varying coefficients, and include variables such as population size, unemployment rate, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (5). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Appendix B Detailing the Background

Commodity Boom. Commodity booms can be generally defined as a period of high demand for commodities which translates into sustained increasing prices over some years. During 2004 to 2013, in particular, the world experienced a period of high international prices for several commodities, agricultural to mineral to energy. This period of sustained prices can be understood as a consequence of high demand from Asia, in particular China, which grew approximately 10% per year and demanded raw materials (WorldBank, 2021). Prices shifted upwards to a new level in real terms when compared to pre-2004 levels, as shown by Figure 1a.

ABC Program. The *Agricultura de Baixo Carbono* (Low Carbon Agriculture) Plan was developed between 2009 and 2010 as *Plano Setorial de Mitigação e de Adaptação às Mudanças Climáticas para a Consolidação de uma Economia de Baixa Emissão de Carbono na Agricultura* — translated as "Sectoral Plan of Mitigation and Adaptation to Climate Change for the Consolidation of a Low-Emission Agriculture". The plan comprises a relevant part of Brazil's effort for reducing greenhouse gas emissions and was set up after the 15th Conference of Parties — COP15 in Copenhagen, in 2009. Voluntarily, Brazil took in the responsibility of decreasing its greenhouse gas emissions by 36.1% to 38.9% until 2020. Our estimates from the Climate Observatory's SEEG show, however, that Brazil's municipalities in total have increased gross GHG emissions from 2010 to 2017 by approximately 20.9%. The ABC program is regulated by Federal Decree number 7.390/2010, which set the objectives, organization, and actions to be taken for the execution of the plan. According to the Brazilian Ministry of Agriculture, Livestock and Supply (MAPA, 2021), the ABC program is composed by seven initiatives — out of which six refer to mitigation technologies and one relates to adaptation. These initiatives are: (i) restoration of degraded pasture-land; (ii) implementation and expansion of integrated systems (agriculture-livestock-commercial forests) and agriforestry systems; (iii) implementation and expansion of no-till systems; (iv) implementation and expansion of biological nitrogen fixation; (v) implementation and expansion of planted forests (commercial and reserves); (vi) implementation and expansion of animal waste treatment systems; (vii) implementation and expansion of climate-change adaption measures. In practice, the plan offered a subsidized credit line to farmers who wanted to implement one or more of the latter. Through Brazil's *Plano Safra*, which every year offers farmers with credit lines for operating and investment loans, the ABC program became a feasible and measurable policy. Farmers may finance investments in techniques and machinery related to the seven initiatives — which led the ABC line to compete with previously existing credit lines that did not have sustainable-or-low-carbon goals. According to our estimates from Brazil's Central Bank, the ABC program has lent approximately 8.2 billion *reais* to farmers over 2013-2017. Although likely the most relevant policy of the ABC plan, the credit line is not the only tool available for implementing the seven initiatives: marketing campaigns, technology transfers, improving the availability of inputs for farmers, research and development, rural insurance, and climatic intelligence are also tools which the ABC Plan has used to achieve its objectives.

Appendix C Detailing Tables and the Robustness Checks

For a better sense of both commodity exposure indexes explained in Section 2, we plot exposure maps for base year 2010, when commodity prices were at a high point in the supercycle. One can see the maps in Figure A.1 below. We proceed in showing Table A.1, in which one can see the summary statistics of all variables taken into consideration in our dataset. Columns "Statistic" and "Unit" describe respectively the variable and its unit of measurement, while column "N" shows the number of observations and the other columns present some basic statistics. The last three lines in this table show the commodity exposure indexes (CE) we utilize in our estimations and robustness checks described below. Table A.2 presents the number of municipalities in Brazil which produces each of the agricultural products in column "Produce"—this is relevant to demonstrate the amplitude of the agricultural commodities chosen in our empirical strategy.

We present Tables A.3 through A.29 with our robustness checks and additional results. We first present Tables A.3 and A.4 with alternative commodity exposure measures—which we describe further below. Next, we perform an inference assessment proposed by Adão et al. (2019) to account for possible cross-regional correlation in the error terms in our regressions; we display the results in Table A.5. In addition, we run another inference assessment by Ferman (2021), in order to identify possible over- and under-rejection of the null. Results are given in Table A.6. We then run a multiple hypothesis test since we have several regressions in our main results; results are given by Table A.8. Finally, we cluster the standard errors into micro-regions and meso-regions for deforestation, the number of fires, net GHG emissions, and ABC credit in Table A.7. Next, we aggregate our analysis into 510 micro-regions following IBGE's classification to take into consideration possible spillover effects among neighboring municipalities and we display the results in Table A.25. We then perform a pre-trends analysis with proxies in Table A.9 to show that deforestation inside farms and change in forested area in municipalities—both proxies for total deforestation prior to our period of analysis—corroborate our findings. Subsequently, we performed a sensitivity test for a period in which the commodity boom had not yet reached sustainable levels—shown in Table A.10. In Table A.11 we run a Poisson fixed effects regression to account for a discrete specification for our main results on the number of fires. As shown, the response of the number of fires to the commodity exposure index remains positive and significant. We also construct Table A.12 in which we demonstrate a first difference approach to our main dependent variables following:

$$\Delta y_i = \beta \Delta CE_i + \gamma \Delta X_i + \eta \Delta W_i + \varepsilon_i \tag{3}$$

where we follow the same specification as in Equation (1) but only for years 2013 and 2003—respectively a year of considerably high prices for agricultural commodities and the beginning of the commodity cycle. We next run three placebo tests. First, we select mining data on Brazilian municipalities which collect a yearly mining tax—CFEM (*Compensação Financeira pela Exploração de Recursos Minerais*)—and we utilize it as a proxy for shares in a new commodity exposure index calculated following Equation (2) using iron ore international prices from the World Bank Pink Sheet in *reais*. Importantly, iron ore represents more 75% of Brazil's mining production and about 70% of all mineral extraction takes place in 10 municipalities—out of which all are iron ore producers. We display the results in Table A.17. Second, in Table A.15 we select municipalities with over 95% urbanization rates in more established states (SE, SP, SC, RJ, RS, RN, PE, PR, PB, MG, ES, CE,BA) to show that those areas are not subjected to deforestation nor fires nor net GHG emissions nor ABC credit when more exposed to commodity booms. In Table A.16, we select municipalities only from São Paulo (SP) state, which is the richest in the country and has been settled mostly in the 1800s. These results also fall within our expectations, showing smaller insignificant coefficients (sometimes with opposite signs). As mentioned in the article, we then present Tables A.18 through A.23 which give detailed results for Figures 2 through 7, respectively. In such tables we show coefficients for $log+1$ and $asinh$ (the hyperbolic inverse sine transformation), and we also present controls, number of observations, and whether estimations had fixed effects. The results largely continue statistically significant. We then test for different log specifications—as described in Section 2—in Table A.24 and perform an exercise with MCAs—*Áreas Minimamente Comparáveis*—in Table A.26. Again, our results remain largely robust. Finally, we switch our dependent variables to the per capita level in Table A.27, to the per hectare level in Table A.28, and to the rural establishment level in Table A.29.

Below, we describe the alternative commodity exposure indexes used to test the robustness of our main specification given by Equation (1)—the results given in Tables A.3 and A.4. First, we perform an estimation inspired by Benguria et al. (2021), who define a regional commodity index as the weighted average of individual commodity prices. We call this commodity exposure 2. The authors utilize employment shares for each commodity with individual commodity prices, as given by the following equation:

$$p_{rt} = \frac{\sum_{c\in C} p_{ct} e_{cr}}{\sum_{c\in C} e_{cr}} \tag{4}$$

where p_{ct} stands for the price of commodity c in period t, and e_{cr} represents the base-year employment of commodity c in region r. In our case, due to data constraints, we use as base-year employment in 1995, which is when the agricultural census took place. Moreover, we perform the estimation taking into account employment in sectors, not for individual commodities as done by Benguria et al. (2021). We divide agricultural employment in three sub-divisions: temporary crops, permanent crops, and livestock. We define sugarcane, maize, soybeans, and rice as temporary crops; banana, cocoa, coffee, and oranges are defined as permanent crops; and beef-cattle is considered livestock. We use the average prices per ton for each of those crops and livestock for calculating the index in Equation (4). Table A.3 below shows our results for this specification. All our previous results remain significant.

In addition, we perform another robustness check inspired by Fiszbein (2021) to build a fractional multinomial logit commodity exposure model given by:

$$CE_{it} = \sum_{k} \hat{Q}_{ki} log P_{kt} \tag{5}$$

for crop or livestock k at time t in municipality i, where $\sum_k \hat{Q}_{ki} = 1$ by construction and its functional form follows:

$$\hat{Q}_{ki} = E[Q_{ki,T}|A_i] = \frac{\exp^{\beta_k A_i}}{1 + \sum_{j=1^{K-1}} \exp^{\beta_j A_i}} \tag{6}$$

where A_i represents crop-specific potential yields in tons per hectare per year given by the FAO-GAEZ soil-and-climate-based productivity measures. One can see the results in Table A.4 below. We call this commodity exposure 3. Again, all our results continue valid under this specification.

It is important to highlight that potential yields are crop-specific and rely mainly on exogenous geo-climatic features—like weather and soil characteristics. As for potential yields for cattle, we follow Laskievic (2021) in using yields for pasture as a proxy for livestock productivity—emphasizing the importance of pasture-based systems for livestock raising in Brazil. Potential yields are estimated in a model using different choices of water supply and levels of technology. The FAO-GAEZ documentation shows pasture-land productivity is estimated using the same methodology as for other crops, accounting also for different species of grass—such as those which are C3 or C4 (Fischer et al., 2021).