Commodity Booms and the Environment

Daniel Da Mata Mario Dotta *

July 28, 2022

Abstract

This paper studies how production responses from agricultural commodity booms affect greenhouse gas emissions, the primary cause of climate change. Using novel data and a shift-share strategy, we show that Brazilian localities more exposed to booms exhibit substantially increased deforestation and agricultural fires, leading to higher emissions. The effects are significantly larger in Brazil's Cerrado than in other biomes. Commodity booms also lead to production responses toward lower emissions, such as higher output per area. Taking into account higher- and lower-emission production responses, high-exposure localities show an increase in net emissions. Moreover, our findings highlight that positive economic shocks may have unintended consequences, as high-exposure localities present lower adherence to an emission-curbing policy.

Keywords: *Economic growth, Environment, Greenhouse gas emissions, Climate mitigation policies, Commodities*

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

*Da Mata: Sao Paulo School of Economics–FGV. Email: daniel.damata@fgv.br. Dotta: Sao Paulo School of Economics–FGV. Email: mariomdotta@gmail.com. We are grateful to Ariel Akerman, Juliano Assunção, Luiz Brotherhood, Leonardo Bursztyn, Bladimir Carrillo, Tiago Cavalcanti, Luiz Fontes, Bernardo Guimaraes, Gordon Hanson, Thiago Lobo, Bruna Mirelle, Romero Rocha, Cezar Santos, Edson Severnini, Arthur Viaro and participants at various seminars and conferences for their helpful comments and suggestions. Dotta gratefully acknowledges financial support from *Instituto Escolhas*. The usual disclaimer applies.

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 recurring 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 GHG emissions being a pressing global challenge, systematic evidence on how periods of economic boom affect these emissions is rather scarce. This paper aims at filling this gap by making two contributions. First, we provide an in-depth analysis of the pathways through which economic growth affects GHG emissions. Second, we investigate the effects of macroeconomic conditions on environmental policies by assessing how economic booms affect take-up of climate mitigation policies.

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 emissions over the past 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

[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 Section 2.

[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, the use of fires by agricultural producers to clear land and promote deforestation is a pervasive feature in many countries.

to deforestation and fires in new and existing agricultural areas. Alternatively, booms may increase production intensity, which would lead to lower 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, booms leading to land-use conversion away from livestock and toward a lower-emission crop mix would lead to lower GHG emissions. Since carbonizing and decarbonizing factors generate conceptually ambiguous effects, the environmental impact of commodity booms is 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 time-series variation of international commodity prices and the spatial variation in agricultural suitability (based on agro-climatic variables). We start by showing that localities more exposed to the commodity boom increase production, as measured by a positive impact on local gross domestic product (GDP). Using satellite data, we find that greater exposure generates measurable effects on deforestation and fires. Specifically, the elasticity of deforestation and fires with respect to the commodity exposure index is about 0.8 and 0.4, respectively.

To further understand the role of carbonizing and decarbonizing factors, we assess the impacts on production intensity, land-use conversion, and crop mix. We find an increase of crop output per hectare (a decarbonizing factor), but land allocation shifts toward a higher-emissions crop mix. In addition, we also find an increase in pasture areas for cattle-raising activities, 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.[5] 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 (e.g., Goldsmith-Pinkham, Sorkin, & Swift, 2020; Borusyak,

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

[5]We also show that net GHG emissions *per hectare* (a measure of emissions' intensity relative to input use) increased in high-exposure municipalities.

Hull, & Jaravel, 2022). 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 empirical specifications, and alternative standard errors' clustering.

Our second contribution is to assess how commodity booms affect adherence to climate change mitigation policies. The importance of these policies is not specific to Brazil: many governments worldwide have been implementing policies to incentivize mitigation (UNEP, 2019). More specifically, we investigate how commodity exposure affects take-up of the ABC (*Agricultura de Baixo 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.[6] Our findings indicate that areas with more exposure to the commodity boom reduced the take-up of ABC credit. The results suggest then that high-exposure localities present lower adherence to this emission-curbing policy. Next, we present suggestive evidence of potential mechanisms that could be underlying these novel findings. The effect seems to be driven by a lower adoption of environmentally friendly management practices in high-exposure 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).[7] 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, within this literature, this paper is unique in showing that economic booms can further lead to environmental deterioration by affecting the adoption of policy-driven mitigation.

We also relate to the literature on climate change mitigation policies. Importantly, studies suggest that, while legislation may be an effective way to put policies in place, voluntary adherence to climate policies usually tends to be ineffective (e.g., Haug et al., 2010; Eskan-

[6]The program funds sustainable agricultural practices (such as restoring degraded pasture land and implementing commercial forests) and the purchase of machine and equipment related to sustainable practices.

[7]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).

der & Fankhauser, 2020; Fekete et al., 2021).[8] In particular, our work is 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 adherence to climate mitigation policies. Our paper also adds another piece of evidence by examining a potential mediator (management practices) explaining the lower adherence to the emission-curbing policy. These findings have far-reaching implications for topics beyond conservation by highlighting how a macroeconomic context interferes with the adoption of 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. This is important because biomass burning is a significant contributor to emissions (Wake, 2021), and fires are a growing environmental stressor in many countries, like the United States. 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; Assunção, Lipscomb, Mobarak, & Szerman, 2017; Zhang, Zhang, & Chen, 2017; Dornelas & Chimeli, 2019). We complement this literature by studying GHG emissions (a worldwide negative externality) related to deforestation and fires.

The remainder of this paper is organized as follows. Section 2 provides some background on Brazil's agricultural sector, the commodity boom, and the ABC Plan. Section 3 describes the empirical strategy. Section 4 presents the data, while Section 5 shows the results. Section 6 concludes.

2 Background

2.1 Agriculture and the Commodity Boom

In the 2000s and 2010s, the world experienced a period of high international prices for several commodities, from agriculture to minerals to energy. This period of sustained higher prices (known as a "commodity boom" or "commodity supercycle") was triggered by in-

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

creased demand from Asian countries, especially China—whose consumption of raw materials grew at an intense pace of approximately 10% per year (WorldBank, 2021). As a result, prices shifted upward to a new level in real terms compared to the 1990s. China has been Brazil's number one trading partner since 2009 (Valls Pereira, 2017).

During this period, the Brazilian economy experienced an increase in several indicators of economic activity, with data showing robust economic growth, especially from 2003 to 2012 (IMF, 2013). Over the past decades, the country has also become a leading producer and exporter of several of the world's most consumed commodities, such as soybeans, maize, and beef (FAOSTAT, 2020). Production is historically concentrated in consolidated areas of agricultural activity. However, it has expanded over unexplored areas in the past decades, such as the Center-West region (which hosts the Cerrado biome) and the Northern region (which hosts the Amazon biome). During the commodity boom period, agricultural output also increased: agricultural areas grew approximately 16% in 2001–2017 (MapBiomas, 2021), and output rose considerably (e.g., soybeans and maize output increased by more than 150% in those years).

This increasing agricultural production associated with the boom may have resulted in pressure against the environment—a hypothesis we formally investigate below. However, the impacts of the agricultural booms on environmental outcomes are conceptually ambivalent: the relative strength of carbonizing and decarbonizing factors will ultimately drive the impacts on the environment. Deforestation, for instance, is a carbonizing factor that has been an acute challenge over the past decades: deforestation in the Amazon and Cerrado biomes from 2001–2017 equaled 521,000 square kilometers (greater than the size of Spain). Most of these new open areas were occupied by agriculture.[9] Data also show that deforestation and land use correspond to approximately 55% of GHG emissions in Brazil during the past two decades. By contrast, some characteristics of Brazil's agricultural sector are associated with carbon sequestration (decarbonizing factors). For instance, agricultural productivity has increased substantially (up to 40%), reflecting technology adoption and better machinery for planting, seeding, and fertilizing.

2.2 ABC Credit Program

Governments throughout the world have been implementing policies to reduce greenhouse gas emissions, the so-called climate change mitigation policies (UNEP, 2019). As a commitment to multilateral cooperation in limiting the increase in global temperatures,

[9] Areas were estimated using official data from PRODES and Terrabrasilis for deforestation, and MapBiomas data on farming and pasture land. See Section 4 for more detail on the data.

Brazil has pledged to cut emissions. The leading initiative to boost sustainability and reduce the country's carbon footprint is the *Agricultura de Baixo Carbono* Plan.[10]

Established in 2010, the ABC Plan is composed of several initiatives (programs) of the Brazilian national government, such as rural credit, insurance, climatic intelligence, and marketing campaigns toward sustainable agricultural activities. In this paper, we focus on rural credit for two reasons: it is the main program of the ABC Plan and the one more suitable for our research question. Notice that the other initiatives of the ABC Plan were not fully implemented (ObservatórioABC, 2020). The primary legislation governing the ABC credit program is Federal Decree number 7,390/2010, which sets the objectives, organization, and actions to execute the program.

The green finance program aims to shape producers' behavior to take into account externalities that affect the environment. More specifically, it provides subsidized credit for (low or net-zero emissions) management practices and investments in farming and livestock. The ABC finances several production techniques such as no-till planting; converting degraded pastureland into productive pasture or crops; and implementing integrated systems (crops, livestock, and planted forests), 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).[11]

Farmers can apply for credit lines for operating and investment loans from the ABC credit program in all major banks in Brazil—which led the ABC credit line to compete with previously existing credit lines that did not have sustainable or low-carbon goals. According to the data, the ABC credit program has lent approximately 8.3 billion *reais* to farmers from 2013 to 2017—representing 10.7% of total investment credit for agriculture in the period.

3 Empirical Strategy

Our interest is to assess if the commodity boom affected environmental outcomes and adherence to a climate mitigation policy. The 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

[10] In Portuguese, the ABC Plan'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*.

[11] The program also funds the implementation and the expansion of climate change adaptation measures.

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 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 factors, as well as adherence to the ABC mitigation policy. 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 η_t is the time-varying coefficient of initial municipal characteristics W_i (a set of pre-boom socioeconomic variables such as population size, poverty rate, and illiteracy rate). All municipalities have equal weights. In addition, since the variation we measure occurs at the municipal level and errors may be correlated within the spatial units, standard errors are clustered at the municipal level to allow for arbitrary variance-covariance structure within municipalities.

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 “agriculture suitability” shares and commodity prices as follows:

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

where the term q_{ki} is the suitability share for crop or livestock k, which sums up to 1 across a given k. P_{kt} is the real international commodity prices for crop or livestock k at time t.

To build (arguably exogenous) agriculture suitability shares q_{ki}, we follow three steps using data from FAO-GAEZ (Food and Agriculture Organization’s Global Agro-Ecological Zones). First, we obtain the potential yield (A_{ki}) for each crop or livestock k in municipality i. The potential yield is a time-invariant measure of the maximum output given climatic (temperature, rain, and humidity) conditions. For a given land area, the potential yield for a crop or livestock is calculated as if that crop or livestock occupied the entire area. Therefore, if one considers several crops and livestock, there is "double counting."

The second step consists in circumventing the double counting by applying Fiszbein (2022)’s procedure to create output weights (based on a model of crop choice). The intuition is to obtain “predicted” output weights using the fact that observed output shares w_{ki} of each crop or livestock k in total agricultural production of municipality i is strongly induced by climatic features. More precisely, we utilize a fractional multinomial logit model—specified as a system of equations in which the outcome variables are each w_{ki}—to calculate the predicted output weight estimating the parameters by quasi-maximum-likelihood as follows:

$$\hat{w}_{ki} = E[w_{ki}|\mathbf{A_i}] = \frac{\exp^{\beta_k \mathbf{A_i}}}{1 + \sum_{j=1}^{K-1} \exp^{\beta_j \mathbf{A_i}}} \tag{3}$$

where $\mathbf{A_i}$ represents the vector of product-specific potential yields. Our outcome variable $\hat{w}_{ki}$ is estimated using the quantity share of production of each crop k for municipality i for a pre-boom period (i.e., the average output of each product from 1996 to 2000). By construction, the predicted weights for each municipality add up to 1, that is, $\sum_{j=1}^{K} \hat{w}_{ki} = 1$.

We then multiply the estimated weight $\hat{w}_{ki}$ and the potential yield A_{ik} to obtain the (weighted) output potential $\bar{Q}_{ki}$ in tons of production of k in municipality i. Finally, the third step to calculate q_{ki} is to transform $\bar{Q}_{ki}$ into a share of production for crop or livestock k in municipality i relative to the rest of the municipalities that also produce k. In sum, the agriculture suitability shares q_{ki} uses a (weighted) measure of maximum production based on climatic variables.

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—for example, places in which the increase in international prices matched their climatic-driven 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; Borusyak et al., 2022). The shift variable (international commodity prices), however, is assumed to be exogenous to local conditions: increase in prices in our period of analysis was triggered by worldwide demand for food and mineral commodities that is likely to be independent of local conditions of a particular municipality.

We provide several specification checks on the plausibility of the identifying assumption. Moreover, in the robustness exercises, we use three alternative measures of commodity exposure, which employ other pre-boom cross-sectional exposure variables. The first alternative commodity exposure index substitutes the suitability shares q_{ki} in Equation (2) by pre-boom employment shares (as in Benguria, Saffie, & Urzúa, 2021). Our second approach follows Bernstein, Colonnelli, Malacrino, and McQuade (2021) and substitutes the shares q_{ki} by pre-boom quantity shares. Finally, our third alternative measure includes only the FAO-GAEZ potential yields in the shares q_{ki}. See Appendix B for a detailed description of these three alternative measures.

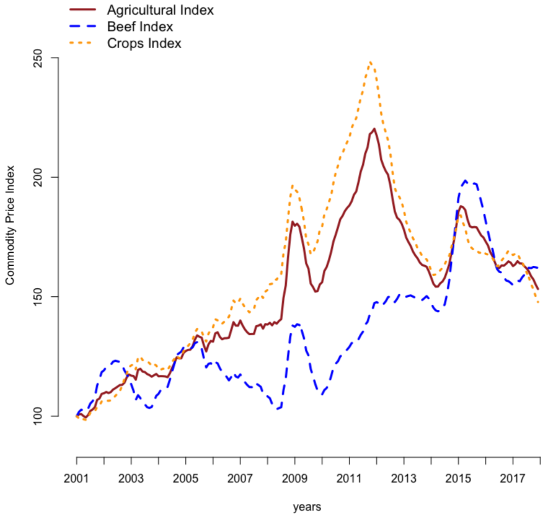
Standard error clustering in shift-share designs could result in over-rejection due to the possibility of shares being similar among regions with similar sectoral structures.[12] Hence, in the robustness exercises, we cluster the standard errors at the more aggregated spatial units to account for cross-regional 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 apply 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.

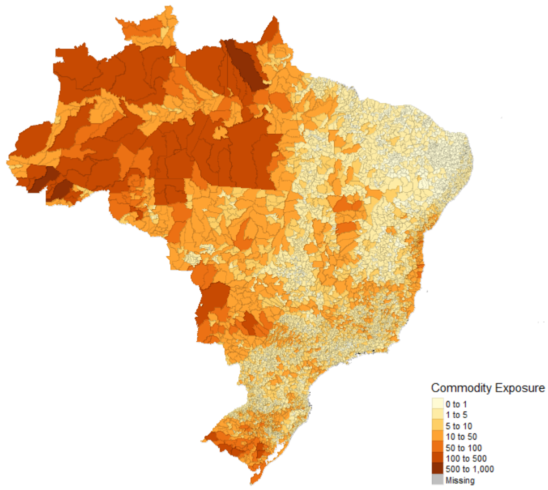
To provide raw patterns from the data, panel (a) of Figure 1 depicts the 12-month moving average of crop prices, beef prices, and overall commodity prices. Panel (b) displays the baseline commodity exposure index. A relevant increase in commodity prices occurred during our period of analysis. In addition, exposure to the commodity shock seems to be widespread across Brazil's municipalities. Finally, 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 group of 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 experience a different pattern motivates a more systematic analysis of the role of booms in guiding emissions.

[12]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 soybean and maize production regions.

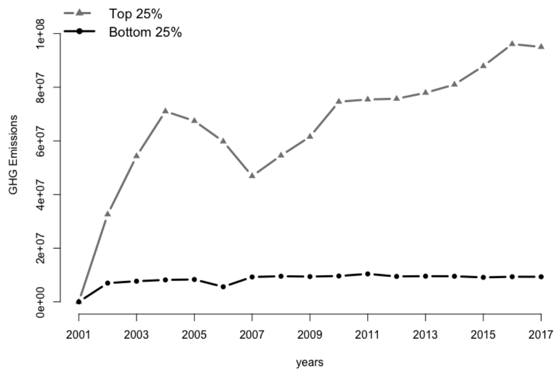
Figure 1: Commodity Prices, Exposure Index, and GHG Emissions



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



(b) Commodity Exposure Index (2010)



(c) Raw Patterns in the Data: GHG Emissions by Commodity Exposure

Notes. Panel (a) presents the price index for the most relevant selected commodities we utilize in the exposure index (e.g., soybeans, maize, bovines). 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 FAO-GAEZ and IBGE and is further described in Section 3. GHG emission data is from Brazil's Climate Observatory.

4 Data

We describe the data in three blocks related to the main empirical specification (Equation (1)): environmental outcomes, commodity exposure index, and other data. Unless otherwise noted, we use data at the municipality-year level from 2001 to 2017.

4.1 Environmental Outcomes

Greenhouse gas emissions. Data on GHG emissions and removals ("sinks") are from the Climate Observatory's *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 (CO_2), methane (CH_4), nitrous oxide (N_2O), 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, crop burning, 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 is 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).

Number of fires. Satellite data on fires are 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.[13] The satellite data allow for comparisons among municipalities over time.[14] We aggregate the pixel-level fire counts to calculate the number of fires at the municipality-year level.

Deforestation. Satellite data on deforestation are from INPE's PRODES for municipalities in the Amazon biome and INPE's Terrabrasilis for municipalities in the Cerrado biome (INPE, 2021a; INPE, 2021b). The Amazon and the Cerrado represent approximately 73% of

[13] A fire inside a pixel is counted as "one fire" whether its size is equal to the minimum detectable area (30 meters 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).

[14] 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 was the AQUA_M-T with sensor MODIS, which captured images at the beginning of the afternoon.

the country's territory. These two databases measure the yearly deforested area in square kilometers for each municipality. For municipalities in the Cerrado biome, the 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 2013 on.

Climate mitigation policy: 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 are 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 credit for sustainable agricultural investments and management practices. The credit data are only available for the period 2013 to 2017. All nominal variables are set to 2010 constant (real) values.

4.2 Commodity Exposure

FAO-GAEZ. Potential yields are based on the agronomical potential of each crop taking into account climatic conditions (temperature, rain, and humidity). According to the model documentation (Fischer et al., 2021), potential yields' calculation assumes that the best suitable land will be used in each grid cell—each grid is composed of an area of 9 kilometers by 9 kilometers. The potential yield for each crop is aggregated across the grid cells of each municipality, providing us with total crop potential yield at the municipal level. We perform this procedure for the following crops: banana, barley, citrus, cocoa, coffee, cotton, groundnut, maize, rice, rubber, sorghum, soybeans, sugarcane, tea, tobacco, and wheat. For estimating the potential yield of bovines per hectare, we utilize the total average yield of grass, and consider the amount of dry weight grass needed to raise one bovine head.[15]

Crop and livestock production. The observable output shares of the commodity exposure index stem from two datasets from the Brazilian Bureau of Statistics (IBGE): *Pesquisa Pecuária Municipal* and *Pesquisa Agrícola Municipal*. We collect information on crops and livestock (in tons and number of heads, respectively) produced in every municipality from 1995 to 2000. We select the same crops and livestock as in the FAO-GAEZ data. The selection includes temporary crops, permanent crops, and livestock based on their impor-

[15]One bovine head needs to eat daily 2.3% of its live weight (230 kilograms per head) to fully express its potential weight gain. For most crops (e.g., soybeans, maize, and wheat), potential production is given in kilograms of dry weight per hectare. For grasses (e.g., alfalfa and napier grass), yields are given in 10 kilograms of dry weight (above ground biomass) per hectare. For sugar beet and sugarcane, production is given in kilograms of sugar per hectare. Cotton yields are given as kilogram lint per hectare.

tance in total production—they represent approximately 85% of agricultural production value per year, according to IBGE data—and their cultivation is widespread across Brazil's regions, as shown in Appendix Table A.2.[16] In addition, we set the commodity exposure index to 2010 constant (real) values using international commodity prices in U.S. dollars from the World Bank (The Pink Sheet), Brazil's consumer price index (IPCA index), and exchange rate data from Ipeadata.

4.3 Additional Data

Municipal GDP data come from IBGE's regional accounts. We are also interested in calculating agricultural productivity (output per hectare), so we match (i) IBGE's *Pesquisa Pecuária Municipal* and *Pesquisa Agrícola Municipal* data with (ii) satellite data on pasture and crop area from MapBiomas—which aggregates and processes granular information (30-meter by 30-meters squares) from the Landsat satellite.

We now describe the data used in the control vectors of our empirical specification. IBGE provides data on the population counts for each municipality, while data on latitude, longitude, temperature, and rainfall come from Da Mata and Resende (2020). The set of demographic data—such as illiteracy rates and the percentage of poor individuals—for each municipality in 2000 is from the United Nations Development Program's *Atlas do Desenvolvimento Humano dos Municípios*.

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

5 Results

We divide the results into six 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 investigate how booms affect climate mitigation policies—the ABC credit program. Next, we perform further analyses, including the results for the Amazon biome. We finish with robustness and specification checks.

[16] 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).

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.

5.1 Effects on Economic Activity, Deforestation, and Fires

We start by showing the effects on economic activity. Figure 2 shows the results for municipal GDP. Localities more exposed to the boom present an increase in GDP: a 1% rise in exposure leads to a 0.10% increase in GDP. The increase in GDP is consistent with production responses from higher international commodity prices and the (mechanical) influence of the higher commodity prices in the GDP calculation. Figure 2 also documents an increase in deforestation and fires in high-exposure localities: an increase of 1% in commodity prices generates approximately 0.8% more square kilometers of deforestation and 0.4% more fires.

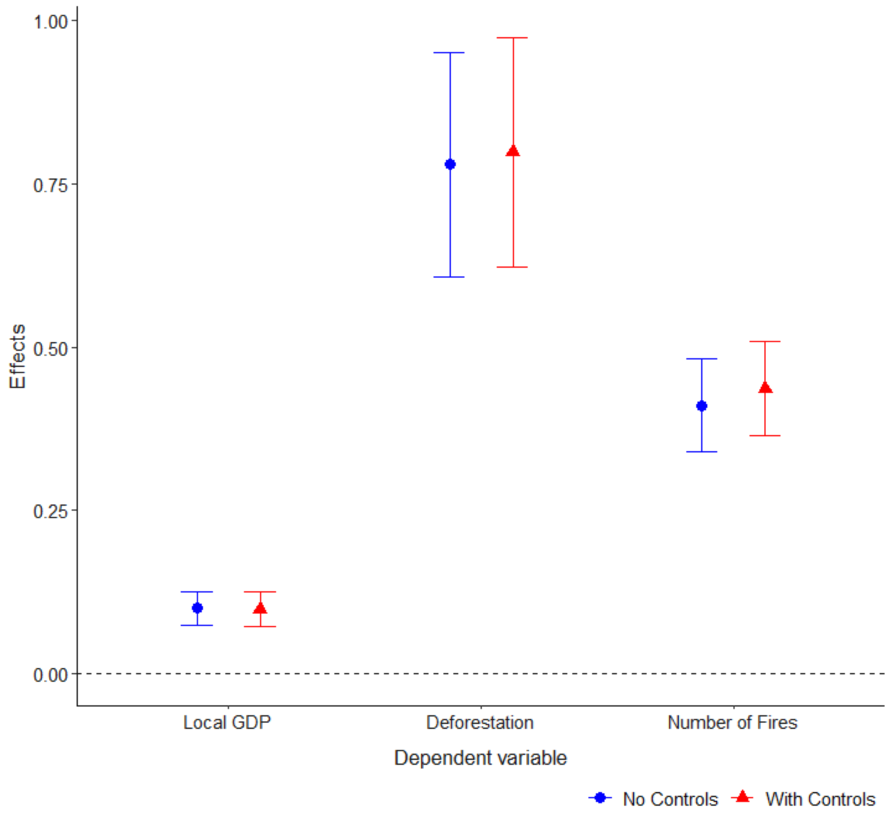
Recall that the deforestation data are only for municipalities in the Amazon and the Cerrado. These biomes have been undergoing the expansion of agricultural activities over the past decades. The relevance of our results resides in showing that commodity booms are related to the expansion of economic activity with further impacts on deforestation and fires. These are strong *carbonizing* effects of commodity booms. Fires are likely related to land clearing for livestock purposes, which we discuss in detail in Subsection 5.5.

5.2 Effects on Carbonizing and Decarbonizing Factors

Beyond deforestation and fires, production responses from commodity booms can lead to further GHG emissions or “market-driven" decarbonization. In Figure 3, we assess the role of land-use conversion between crops and livestock. The estimates show that a 1% rise in exposure increases pastureland by 0.11%. Cattle raising is often associated with higher GHG 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 cattle counts over hectares allocated to pastureland—has decreased in areas more exposed to commodity booms. This is consistent with the idea that rising prices generate an incentive for area expansion, which takes place by increas-

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



Notes. This figure presents the results from the estimation of Equation (1) for three dependent variables: “Local GDP", “Deforestation", and “Number of Fires". The unit of observation is municipality-year. Local 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.17 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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

ing pastureland—thus reducing productivity per hectare when the number of cattle heads does not keep pace with such area expansion.

By contrast, we find that crop productivity (crop output per hectare) has increased; a 1% increase in commodity exposure is related to a 0.12% increase in crop productivity. As a result, the production intensity in crops leads to lower emissions. We also inspect the role of crop mix and follow a classification of GHG emissions for each crop from Poore and Nemecek (2018). Soybean, orange, maize, coffee, groundnut, wheat, and sorghum 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). However, rice, sugarcane, cocoa, barley, tobacco, latex, and tea are considered high-emission crops. Figure 3 indicates that there has been crop reallocation from lower- toward higher-emission crops; a 1% increase in exposure generates a 0.70% decrease in cropland allocated to 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 emissions as well as promoting mitigation.

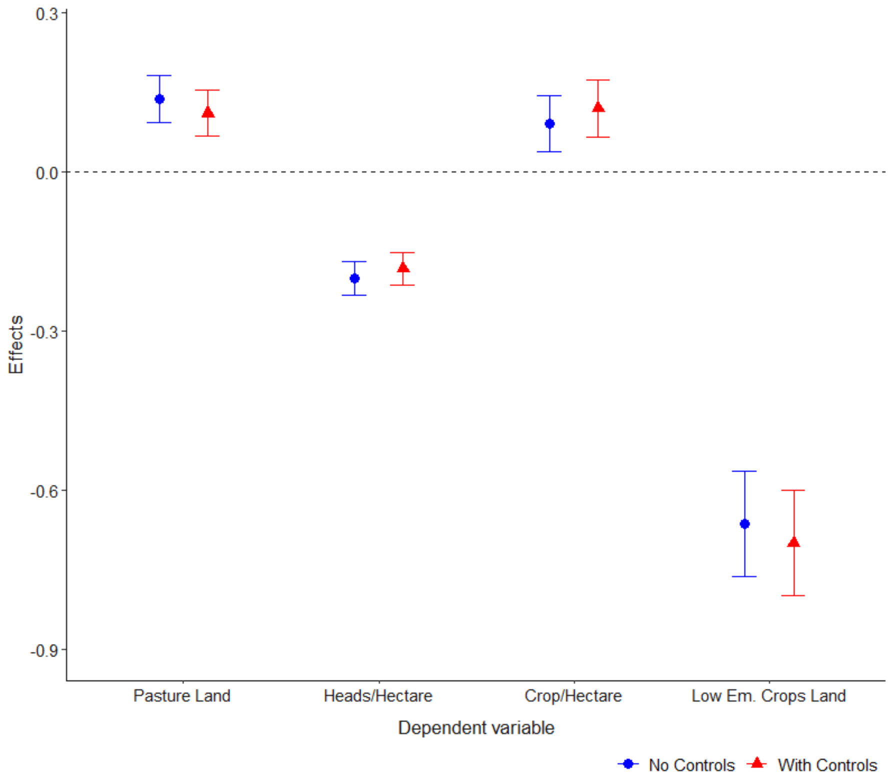
5.3 Effects on GHG Emissions

We now turn to the broad implications of commodity booms for net greenhouse gas emissions. We run our baseline empirical specification with four measures of GHG emissions as dependent variables: (i) total (gross) emissions, (ii) gross intensity emissions, (iii) net emissions, and (iv) net intensity emissions. The intensity measures are given by GHG emissions divided by agricultural area.

Figure 4 reports that high-exposure localities present higher gross emissions. GHG emissions rise about 0.32% 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, after taking into consideration carbonizing and decarbonizing factors, net emissions increase in high-exposure localities. The fact that the magnitude of net emissions is not statistically different from that of gross emissions is consistent with our findings that few production responses are decarbonizing (more precisely, only the increasing output intensity in crops).

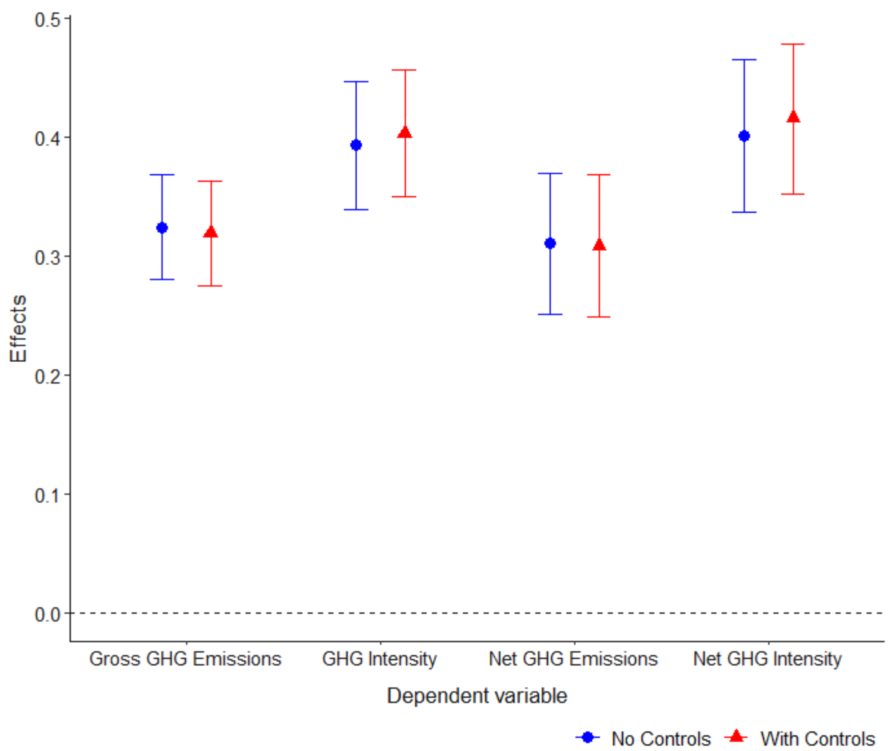
Finally, intensity measures reveal the effects of commodity exposure on the amount of GHG emissions (gross and net) relative to input use. Both gross and net GHG emissions per hectare present high responses to exposure, reinforcing that carbonizing factors are relevant in our context.

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 four dependent variables: "Pasture Land", cattle "Heads per Hectare", "Crop production per Hectare", and "Low Emission Crops". The unit of observation is municipality-year. Low Emission Crops is the area taken by crops that emit less greenhouse gases, and Pasture Land is the area of natural, well-managed, or degraded pasture. Crop production per hectare is in tons per hectare, while cattle heads per hectare is the count of heads divided by hectare. 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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

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", “Gross GHG Intensity Emissions", “Net GHG Emissions", and “Net GHG Intensity Emissions". The unit of observation is municipality-year. Gross and net GHG emissions are measured in tons of CO2eq. for each municipality, while intensity measures are given by emissions divided by agricultural area in hectares. 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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

5.4 Impacts on Climate Mitigation Policy

This subsection assesses how the commodity boom has impacted voluntary take-up of the ABC credit program. Since the program started in 2010 and ABC credit data are available from 2013 on (see Section 4), we analyze the impact of booms on the ABC credit program for the period 2013–2017. More specifically, we run Equation (1) with ABC credit as the dependent variable and data for the restricted period of 2013–2017. As a consequence, we analyze a period of relatively lower crop prices, but increasing beef values (recall Figure 1a).

Figure 5 displays the results. The ABC credit line as a share of total credit was negatively impacted: a -0.16% 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 the green credit line was negatively associated with exposure. One implication from our results is that macroeconomic variables can affect voluntary adherence to climate mitigation policy.

We perform two exercises to understand our results further. In the first exercise, we explore the potential role of pro-environment 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. Seeds are planted over the residues of previous crops by cutting a V-slot, placing the seeds, and closing 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 appropriately in a well-managed pasture, they eat plants that will subsequently grow again—thus capturing more CO_2 in the process. They also leave feces and urine in the fields, reducing the need for fertilizers.[17] However, when well-managed pastureland is not intensively

[17] The specialized literature indicates that under a high-intensity, well-managed pasture, it is possible to produce beef cattle while sequestering CO_2 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 ac-

grazed by cattle, these environment-friendly benefits do not occur.

Our data allow us to compute the percentage area farmers use to practice no-till farming and the percentage area livestock producers maintain as 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. We run the cross-section specification with management practices as the dependent variables.[18]

Our findings suggest that the effect is driven by high-exposure municipalities adopting less environment-friendly management practices. Figure 5 depicts that no-till areas have decreased in high-exposure localities (with controls). Furthermore, such municipalities have also been negatively affected in terms of areas for well-managed pastureland. This result is considerably worse if one takes into account the lower number of heads of cattle per hectare given in Figure 4. This means the remaining well-managed pastureland does not present the environmental benefits it would if properly grazed. The findings are consistent with the fact that the ABC Plan puts emphasis precisely on financing such management practices.[19]

Conceptually, the results can be rationalized by producers facing a trade-off between the adoption of greener, subsidized practices and the longer learning process adoption takes.[20] Strong economic incentives to expand production may increase the opportunity costs of the learning process. As a result, producers in high-exposure localities 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.

Last, the second exercise checks whether GHG emissions have increased in the shorter panel period from 2013–2017. Interestingly, the results from Figure 5 show that emissions continue to present a similar pattern—that is, increases in more exposed localities—as in the previous analysis with the more extended panel.

---

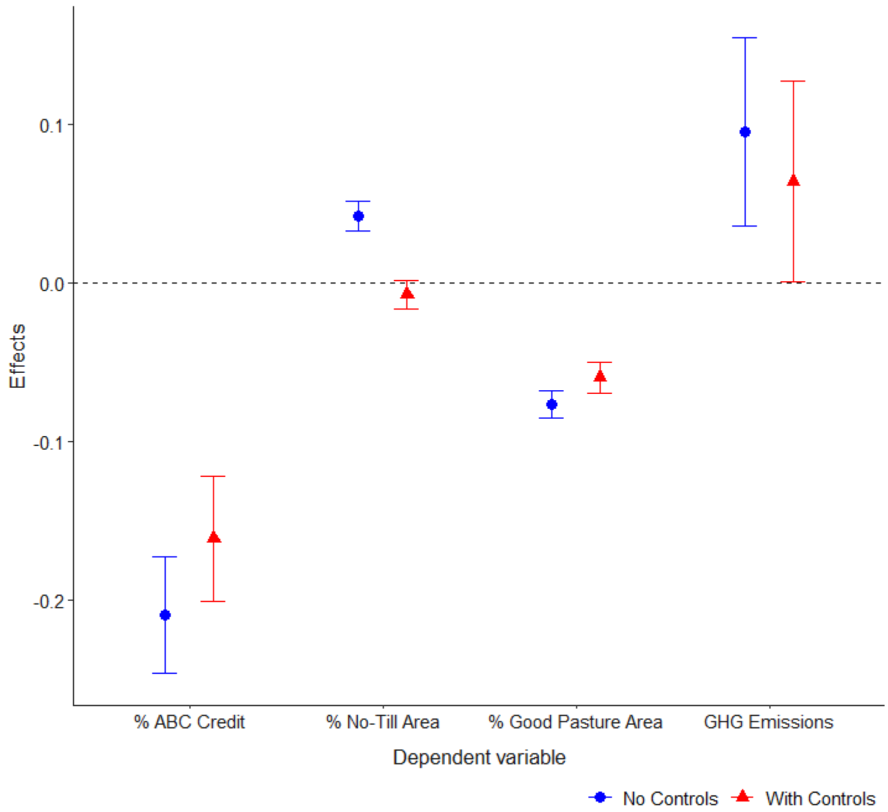
cording to which a farmer grows a commercial forest, a cash crop (spring-summer), and pasture (fall-winter) in the same area to maximize yield.

[18]We use the following equation: $y_i = \alpha + \beta CE_i + \gamma X_i + \eta W_i + \varepsilon_i$, where y_i includes the agricultural practices in 2017, CE_i stands for the commodity exposure index with the (same) time-invariant suitability shares and commodity prices for 2017, X_i is the vector of socioeconomic controls in 2000, and W_i the vector of geo-climatic variables in 2017.

[19]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.

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

Figure 5: Effects of Commodity Booms: adherence to a Climate Mitigation Policy



Notes. This figure presents the results from the estimation of Equation (1) for four dependent variables: "% ABC Credit", "% No-Till Area", "% Good Pasture Area", and "GHG Emissions". The unit of observation is municipality-year for % ABC Credit, and GHG Emissions for years 2013 to 2017. We run a cross-section version of Equation (1) for year 2017 for % No-Till Area and % Good Pasture Area. GHG emissions are measured in tons of CO2eq. % ABC Credit corresponds to ABC credit divided by total credit. % No-Till Area and % Good Pasture Area are measured in percentage points relative to total cropland and pastureland, respectively. The commodity exposure index and GHG emissions are transformed into $log+1$, while the other variables remain in percentage—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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall).

5.5 Further Results

This subsection performs further analysis using the baseline shift-share approach 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 high emissions, high deforestation rates, and more fires as a consequence of the commodity boom. In particular, notice that the point estimates of deforestation and fires are greater in the Cerrado than in the Amazon. A 1% increase in exposure to the commodity cycle is associated with 1.03% more deforestation and 0.6% more fires in the Cerrado. Notice that although fires do not occur naturally in the Amazon, the number of fires is relevant: a 1% increase in exposure results in 0.40% more fires. Both biomes experienced an increase in net GHG emissions. Therefore, these results indicate that the impacts of commodity booms on environmental variables—particularly deforestation and fires—were significant in these two important biomes of Brazil.[21]

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-only exposure index and crops-only exposure index. We find that municipalities presented a higher response to deforestation, fires, and net GHG emissions for beef exposure—notice that in Figure 7 the coefficients from "Bovine" are greater in magnitude than those for "Crop." Collectively, these results suggest that the effects we observe are driven mainly by the livestock sector. The results from cattle-raising exposure relate to the increasing area allocated to livestock and the extensive livestock production we observe (recall Figure 3).

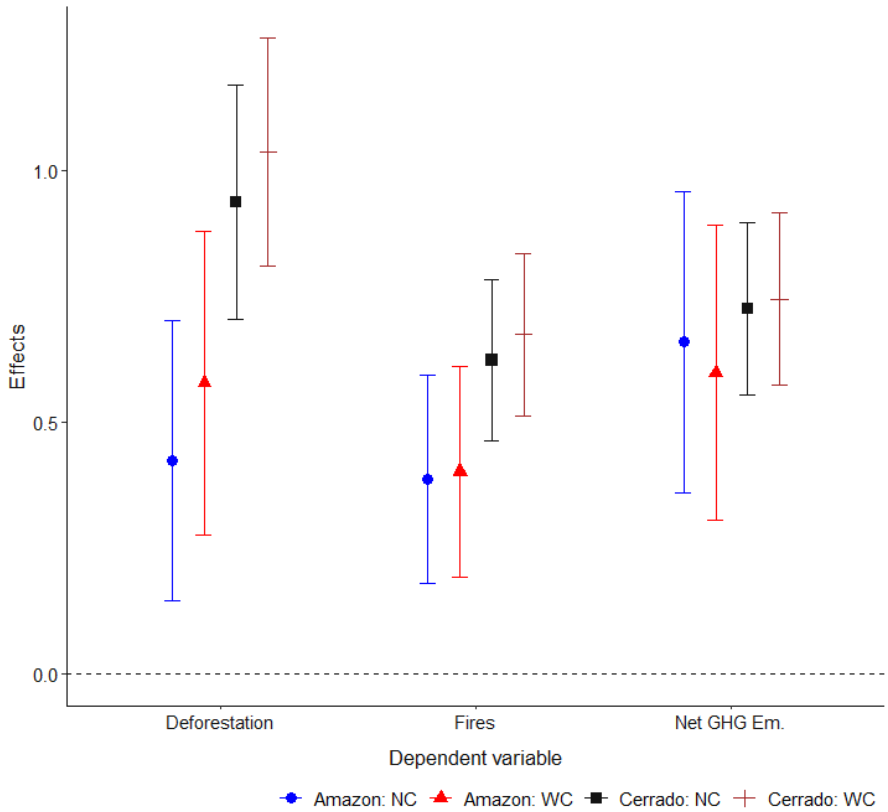
5.6 Robustness and Specification Checks

We perform several robustness exercises and specification tests. Here, 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 mainly on four dependent variables: deforestation, fires, net GHG emissions, and ABC credit.

Alternative commodity exposure indices. We start by using the three alternative definitions of commodity exposure—see Appendix A and Figure A.1 for more details. The results

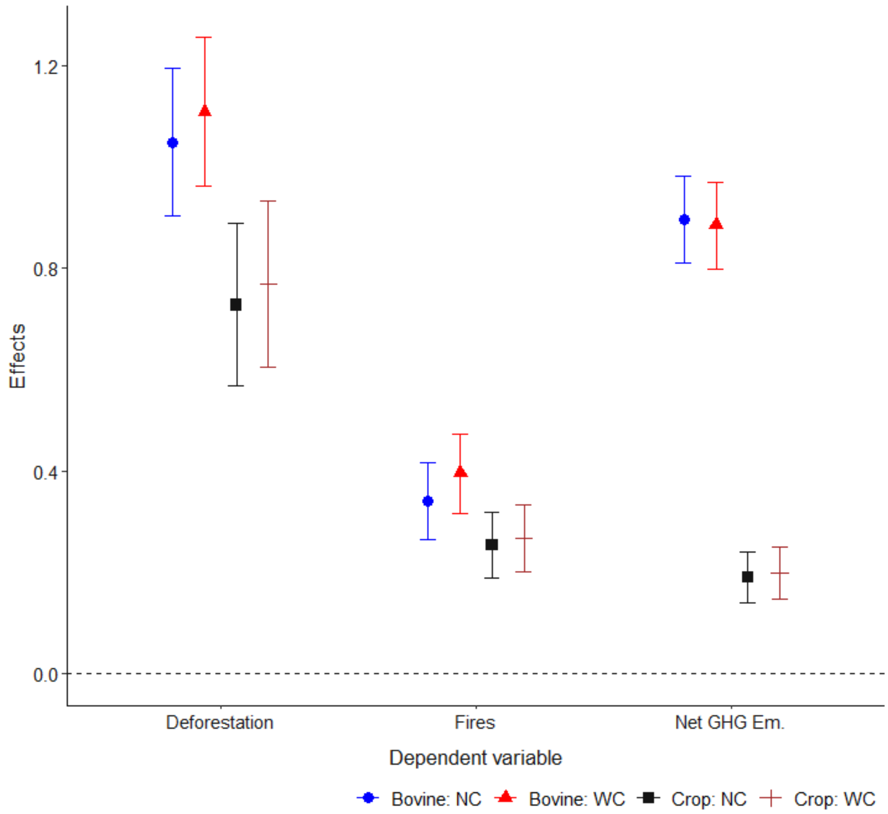
[21] Brazil has six biomes: Cerrado, Amazon, Pantanal, Pampas, Mata Atlântica, and Caatinga.

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.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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall). NC stands for “No Controls" and WC stands for “With Controls".

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 a livestock-only exposure index and crops-only exposure 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 exposure indexes 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, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall). NC stands for "No Controls" and WC stands for "With Controls".

displayed in Appendix Tables A.3, A.4, and A.5 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.6 shows that the significance of the results holds after applying the inference correction. We also performed an inference assessment following Ferman (2021), shown in Appendix Table A.7, which further alleviates concerns of the clustering at the municipal level. Moreover, in Appendix Table A.8, 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 the 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 of the Subsections 5.1–5.4 as a separate "family" (e.g., outcomes in Subsection 5.1 are considered one family of outcomes; outcomes in Subsection 5.2 are considered another family). Within each family, the most significant hypothesis is rejected if the associated p-value is lower than α/S, which is equivalent to a Bonferroni correction. The second most significant hypothesis is rejected if the associated p-value is lower than $\alpha/(S-1)$. Finally, the jth most significant hypothesis is rejected if the associated p-value is lower than $\alpha/(S-j+1)$. Appendix Table A.9 presents the multiple hypothesis-testing exercise. The results strongly support the significance of our main results.

Pre-trends. We perform a dynamic differences-in-differences analysis to study the pre- and post-treatment effects of the commodity boom. More specifically, we estimate the following specification:

$$y_{it} = \sum_{\tau=-j}^{J} \beta_\tau \cdot \left[\sum_k q_{ki} \cdot (\text{Periods After Event=}\tau) \right] + \gamma X_{it} + \eta_t W_i + \mu_i + \delta_t + \varepsilon_{it}, \tag{4}$$

y_{it} is the environmental outcome in municipality i in period t, q_{ki} is the agriculture suitability share for crop or livestock k in municipality i, and μ_i and δ_t are municipality and time fixed effects, respectively. The indicator variable "Periods After Event=τ" takes a value of one τ periods away from the beginning of the commodity boom period and zero otherwise. The vector X_{it} includes time-varying geo-climatic variables, and W_i is the set of socioeconomic variables. Standard errors are clustered at the municipality level. The parameter of interest is β, the effect of being exposed to the boom. Each coefficient β_τ should be interpreted as a change relative to the base period, which is the omitted coefficient $\beta_{\tau=-1}$. We let the year 2002 be the base period.

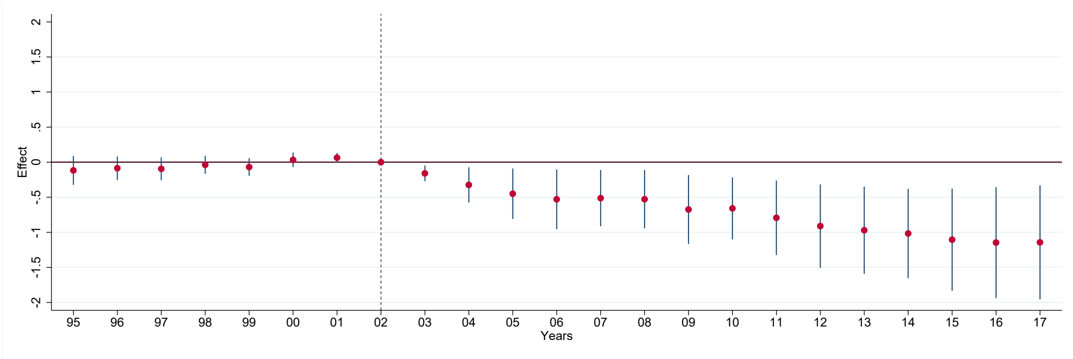
Data constraints do not allow us to use the baseline data on deforestation, fires, and emissions for the analysis before the boom. Therefore, we leverage another dataset in the dynamic difference-in-differences analysis: the MapBiomas dataset, which collects granular information (30-meter by 30-meter squares) from the Landsat satellite between 1985 and 2017 that uses machine-learning techniques to classify the usage of a given pixel of land. Land can be classified into various uses, such as pasture, agriculture, urban, and forest areas. See MapBiomas (2021) for further details. In particular, we use data on forest cover ("Natural Forest Area") in our analysis.

Figure 8 depicts the results when we estimate Equation (4) using forest cover as the dependent variable. This complementary empirical strategy coherently documents a strong increase in deforestation, as measured by a decreasing natural forest cover area. Higher- and lower-exposure localities evolved similarly during the period before the boom, suggesting the absence of different pre-trends in deforestation and supporting the main identifying assumption.[22]

GPSS Test. Although we showed no anticipatory effects in deforestation, other potential threats to our identification strategy and interpretation of our results could still be present. For instance, since our identification assumption is based on exogenous shares, a threat would occur if individual shares could predict the outcomes through channels other than the commodity boom. To provide supporting evidence that our results are unlikely driven by confounding trends, we follow Goldsmith-Pinkham et al. (2020) to calculate the *Rotemberg Weights* for each commodity-specific agricultural suitability share. The intuition of these weights is to capture the degree of sensitivity to misspecification by decomposing the agricultural suitability share q_{ki} into a weighted combination based on each crop or livestock. Appendix Table A.11 shows the Rotemberg Weights for all 14 crops and one live-

[22]To further check pre-trends, Appendix Table A.10 uses the baseline data on deforestation, fires, and net GHG emissions and estimates Equation (1) for the period 2001–2004 when the commodity boom had not yet become fully intense. Results are either not statistically significant or small in magnitude.

Figure 8: Dynamic Difference-in-Differences: Natural Forest Area



(a) Dependent variable: Forest Area

Notes: The figure plots the coefficients from estimating Equation (4). Data on "Natural Forest Area" (Forest Formation plus Savannah Formation) is from MapBiomas. Controls include demographic variables (population size, poverty rate, and illiteracy rate) and geo-climatic variables (temperature and rainfall). Standard errors are clustered at the municipality level. Confidence intervals: 95%.

stock that we utilize in our baseline exposure design.[23] Weights are skewed toward three crops—cocoa, latex, and banana represent up to 47% of the weights.

We perform two checks. First, we test in Appendix Table A.12 whether covariates can explain a larger variation in shares when compared to our baseline exposure shift-share variable. The R^2 are significantly higher for our main outcome variables (deforestation, fires, and GHG emissions) when compared to the R^2 from the relationship of our baseline controls and most relevant shares (latex, cocoa, and banana shares; plus bovine, soybean, and maize shares, which are shown due to their importance to Brazil's agricultural sector). Second, we check for pre- and post-treatment effects for each individual crop or livestock using the dynamic difference-in-differences specification (Equation (4)) and natural forest area as the dependent variable. Figure A.2 shows results for latex, cocoa, and banana, plus bovine, soybeans, and maize. Again, there are no significant pre-trends (except for soybean). Hence, our tests broadly suggest that our findings are unlikely to be driven by confounding trends. Moreover, the results suggest that no individual crop or livestock is driving the results, as the decrease in forest area is verified overall and does not seem to be driven by any particular crop or livestock.

Other empirical specifications. In Appendix Table A.13, we run a Poisson fixed effects regression to account for the fact that the number of fires is a count variable. Results are

[23]We use 2013 as a cross-section year to estimate the Rotemberg Weights due to the higher prices observed in that year. See the online Appendix for more details on the calculation of these weights.

robust after estimating using that alternative model. We also run a first difference model in Appendix Table A.14. Our baseline results are also robust to this new empirical specification.

Brazil as top producer. Brazil is a major producer and exporter of several commodities (e.g., soybeans, maize, and beef) and thus may affect prevailing prices. Hence, one might consider that some individual commodity could have its price affected by production changes inside one or more of Brazil's municipalities. Therefore, we perform a robustness check in which we exclude from our commodity index from Equation (1) one relevant commodity at a time. Results are qualitatively similar and shown in Appendix Table A.15.

Placebo exercise using mineral booms. International prices of iron ore also increased steeply during our analysis period—as did agricultural commodity prices. 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. In Appendix Table A.16, we run a placebo exercise with mineral production, using municipalities that collected a mining tax—CFEM—to proxy for the importance of such sector in a municipality's economy. We build a new commodity exposure index using lagged shares of CFEM collection and data on iron ore prices, the most widespread mining commodity in Brazil. 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 our baseline results use the $log+1$ transformation for the dependent variables and the commodity exposure index. We investigate and find that results are robust when using the alternative hyperbolic inverse sine transformation—see Appendix Tables A.17–A.22. We also test for other log transformations in Appendix Table A.23—see description of these transformation in the online Appendix B. Results remain largely robust for all these checks.

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. IBGE 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 regions, which may be experiencing pressures from the expansion of economic activities. Table A.24 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; in 2000, there were 5,507 (Cavalcanti et al., 2019). From 2001–2017, approximately 50 new municipalities were created. We show in Table A.25 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, and (ii) the agricultural area (hectares) in 2001—see Tables A.26 and A.27, respectively. The results are again largely robust.

6 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 (e.g., deforestation and fires) as well as *decarbonizing* factors (e.g., 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 (that is, decarbonizing factors as “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 tackle climate change. In particular, managing greenhouse gas emissions is key to countering the increase in global temperatures. Our findings on the carbon footprint of booms generated by worldwide demand for food have relevant implications. Carbonizing factors such as deforestation and fires can have adverse impacts by affecting infant, child, and adult health (e.g., Reddington et al., 2015; Rangel & Vogl, 2019; Zivin, Liu, Song, Tang, & Zhang, 2019). Apart from being a significant driver of biodiversity loss, 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 a credit line 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 adherence to mitigation policy is affected by macroeconomic conditions and may need strong incentives to achieve the targeted goals.

References

Adão, R., Kolesár, M., & Morales, E. (2019). Shift-Share Designs: Theory and Inference. *The Quarterly Journal of Economics*, *134*(4), 1949-2010.

Allcott, H., & Keniston, D. (2018). Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America. *The Review of Economic Studies*, *85*(2), 695-731.

Andela, N., Morton, D. C., Giglio, L., Chen, Y., van der Werf, G. R., Kasibhatla, P. S., ... Randerson, J. T. (2017). A Human-Driven Decline in Global Burned Area. *Science*, *356*(6345), 1356–1362.

Assunção, J., Gandour, C., & Rocha, R. (2015). *Deforestation Slowdown in the Brazilian Amazon: Prices or Policies?* (Working Paper). Climate Policy Initiative.

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2020). The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon. *Economic Journal*, *130*(626), 290-330.

Assunção, J., Lipscomb, M., Mobarak, A. M., & Szerman, A. D. (2017). *Agricultural Productivity and Deforestation in Brazil* (Working Paper). Climate Policy Initiative.

Balboni, C., Burgess, R., Heil, A., Old, J., & Olken, B. A. (2021). Cycles of Fire? Politics and Forest Burning in Indonesia. *AEA Papers and Proceedings*, *111*, 415-19.

Balboni, C., Burgess, R., & Olken, B. (2021). *The Origins and Control of Forest Fires in the Tropics* (Working Paper).

Barona, E., Ramankutty, N., Hyman, G., & Coomes, O. T. (2010). The Role of Pasture and Soybean in Deforestation of the Brazilian Amazon. *Environmental Research Letters*, *5*(2), 024002.

Benguria, F., Saffie, F., & Urzúa, S. (2021). *The Transmission of Commodity Price Super-Cycles* (NBER Working Papers No. 24560). National Bureau of Economic Research, Inc.

Bernstein, S., Colonnelli, E., Malacrino, D., & McQuade, T. (2021). Who Creates New Firms When Local Opportunities Arise? *Journal of Financial Economics*, *143*(1), 107-130.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-Experimental Shift-Share Research Designs. *Review of Economic and Statistics*, *89*(1), 181–213.

Bragança, A. (2018). The Effects of Crop-to-Beef relative Prices on Deforestation: Evidence from the Tapajós Basin. *Environment and Development Economics*, *23*(4), 391–412.

Burke, M., & Emerick, K. (2016). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106-140.

Caselli, F., & Michaels, G. (2013). Do Oil Windfalls Improve Living Standards? Evidence from Brazil. *American Economic Journal: Applied Economics*, *5*(1), 208–38.

Cattaneo, A. (2002). *Balancing Agricultural Development and Deforestation in the Brazilian Amazon* (Research reports No. 129). International Food Policy Research Institute (IFPRI).

Cavalcanti, T., Da Mata, D., & Toscani, F. (2019). Winning the Oil Lottery: the Impact of Natural Resource Extraction on Growth. *Journal of Economic Growth*, *24*(1), 79-115.

Chen, S., Chen, X., & Xu, J. (2016). Impacts of Climate Change on Agriculture: Evidence from China. *Journal of Environmental Economics and Management*, *76*(C), 105-124.

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F. N., & Leip, A. (2021). Food Systems are Responsible for a Third of Global Anthropogenic GHG Emissions. *Nature Food*, *2*(3), 198–209.

Da Mata, D., & Resende, G. (2020). Changing the Climate for Banking: The Economic Effects of Credit in a Climate-Vulnerable Area. *Journal of Development Economics*, *146*, 102459.

Dasgupta, P. (2021). The Economics of Biodiversity: The Dasgupta Review. *London: HM Tresury*.

de Azevedo, T., Costa Junior, C., Brandão Junior, A., Cremer, M., Piatto, M., Tsai, D., ... Kishinami, R. (2018). SEEG Initiative Estimates of Brazilian Greenhouse Gas Emissions from 1970 to 2015. *Scientific Data*, *5*(63192).

Dornelas, V., & Chimeli, A. (2019). *China Shock: Environmental Impacts in Brazil* (Working Papers). EAERE 24th Annual Conference.

Eskander, S. M. S. U., & Fankhauser, S. (2020). Reduction in Greenhouse Gas Emissions from National Climate Legislation. *Nature Climate Change*, *10*(8), 750–756.

FAOSTAT. (2020). *Countries by Commodity.* Food and Agriculture Organization. Retrieved 2020-12-21, from http://www.fao.org/faostat/en/#rankings/countries_by_commodity

Faria, W. R., & Almeida, A. N. (2016). Relationship Between Openness to Trade and Deforestation: Empirical Evidence from the Brazilian Amazon. *Ecological Economics*, *121*, 85-97.

Fekete, H., Kuramochi, T., Roelfsema, M., den Elzen, M., Forsell, N., Höhne, N., ... Gusti, M. (2021). A Review of Successful Climate Change Mitigation Policies in Major Emitting Economies and the Potential of Global Replication. *Renewable and Sustainable Energy Reviews*, *137*, 110602.

Ferman, B. (2021). *Assessing Inference Methods* (Working Paper No. 1912.08772). arXiv.

Fischer, G., Nachtergaele, F., van Velthuizen, H., Chiozza, F., Franceschini, G., Henry, M.,

… Tramberend, S. (2021). *Global Agro-Ecological Zones v4 – Model documentation* [Technical Paper]. Food and Agriculture Organization.

Fiszbein, M. (2022). Agricultural Diversity, Structural Change, and Long-Run Development: Evidence from the US. *American Economic Journal: Macroeconomics*, *14*(2), 1-43.

Foster, A. D., & Rosenzweig, M. R. (2003). Economic Growth and the Rise of Forests. *The Quarterly Journal of Economics*, *118*(2), 601-637.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review*, *110*(8), 2586-2624.

Grossman, G. M., & Krueger, A. B. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics*, *110*(2), 353-377.

Harding, T., Herzberg, J., & Kuralbayeva, K. (2020). *Commodity Prices and Robust Environmental Regulation: Evidence from Deforestation in Brazil* (OxCarre Working Papers No. 225). Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Haug, C., Rayner, T., Jordan, A., Hildingsson, R., Stripple, J., Monni, S., … Berkhout, F. (2010). Navigating the Dilemmas of Climate Policy in Europe: Evidence from Policy Evaluation Studies. *Climatic Change*, *101*(3), 427–445.

Holm, S. (1979). A Simple Sequentially Rejective Multiple Test Procedure. *Scandinavian Journal of Statistics*, *6*(2), 65–70.

IBGE. (2019). *Estatística da Produção Pecuária* (Tech. Rep.). Instituto Brasileiro de Geografia e Estatística.

IBGE. (2020). *Produção Agrícola municipal - PAM - Mudança da unidade de medida das frutíferas* (Tech. Rep.). Instituto Brasileiro de Geografia e Estatística.

IMF. (2013). *Unleashing Brazil's Growth.* Retrieved 2022-05-10, from `https://blogs.imf.org/2013/11/27/unleasing-brazils-growth/`

INPE. (2020a). *BDQueimadas.* Retrieved 2020-12-02, from `http://queimadas.dgi.inpe.br/queimadas/bdqueimadas`

INPE. (2020b). *Perguntas Frequentes.* Retrieved 2020-12-02, from `http://queimadas.dgi.inpe.br/queimadas/portal/informacoes/perguntas-frequentes#p9`

INPE. (2021a). *PRODES.* Instituto Nacional de Pesquisas Espaciais. Retrieved 2021-05-20, from `http://www.dpi.inpe.br/prodesdigital/prodesmunicipal.php`

INPE. (2021b). *Terrabrasilis.* Instituto Nacional de Pesquisas Espaciais. Retrieved 2021-05-20, from `http://terrabrasilis.dpi.inpe.br`

IPCC. (2019). Summary for Policymakers. In P. Shukla et al. (Eds.), *Climate Change and Land: an IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems.* In press.

Koch, N., zu Ermgassen, E. K., Wehkamp, J., Oliveira Filho, F. J., & Schwerhoff, G. (2019). Agricultural Productivity and Forest Conservation: Evidence from the Brazilian Amazon. *American Journal of Agricultural Economics*, *101*(3), 919-940.

MAPA. (2016). *Ministério da Agricultura, Pecuária e Abastecimento, Plano ABC, Financiamento.* Retrieved 2021-02-02, from `https://www.gov.br/agricultura/pt-br/assuntos/sustentabilidade/plano-abc/financiamento`

MapBiomas. (2021). *Projeto MapBiomas – Coleção [5.0] da Série Anual de Mapas de Cobertura e Uso de Solo do Brasil.* Retrieved 2021-08-30, from `https://mapbiomas.org/estatisticas`

Michael Kolesár. (2020). *Standard Errors in Shift-Share Regressions* (Notes).

Nordhaus, W. (2019). Climate Change: The Ultimate Challenge for Economics. *American Economic Review*, *109*(6), 1991-2014.

ObservatórioABC. (2020). *Agricultura de Baixa Emissão de Carbono: A Evolução de um Novo Paradigma.* Retrieved 2022-05-10, from `https://ainfo.cnptia.embrapa.br/digital/bitstream/item/117611/1/sumario-estudo-1.pdf`

Oliveira, P. P. A., Berndt, A., Pedroso, A. F., Alves, T. C., Pezzopane, J. R. M., Sakamoto, L. S., ... Rodrigues, P. H. M. (2020). Greenhouse Gas Balance and Carbon Footprint of Pasture-Based Beef Cattle Production Systems in the Tropical Region (Atlantic Forest Biome). *Animal*, *14*(S3), s427–s437.

Panayotou, T. (2000). *Economic Growth and the Environment* (CID Working Papers No. 56). Center for International Development at Harvard University.

Pfaff, A. S. P. (1999). What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic Data. *Journal of Environmental Economics and Management*, *37*(1), 26-43.

Poore, J., & Nemecek, T. (2018). Reducing Food's Environmental Impacts through Producers and Consumers. *Science*, *360*(6392), 987–992.

Rangel, M. A., & Vogl, T. S. (2019). Agricultural Fires and Health at Birth. *The Review of Economics and Statistics*, *101*(4), 616-630.

Reddington, C. L., Butt, E. W., Ridley, D. A., Artaxo, P., Morgan, W. T., Coe, H., & Spracklen, D. V. (2015). Air Quality and Human Health Improvements from Reductions in

Deforestation-Related Fire in Brazil. *Nature Geoscience*, *8*(10), 768–771.

Stern, N. (2008). The Economics of Climate Change. *American Economic Review*, *98*(2), 1-37.

Torres, C. M. M. E., Jacovine, L. A. G., Nolasco de Olivera Neto, S., Fraisse, C. W., Soares, C. P. B., de Castro Neto, F., … Lemes, P. G. (2017). Greenhouse Gas Emissions and Carbon Sequestration by Agroforestry Systems in Southeastern Brazil. *Scientific Reports*, *7*(1), 16738.

UNEP. (2019). *Emissions Gap Report* (Report). United Nations Environment Programme.

Valls Pereira, L. B. (2017). Comércio e Investimento na Agenda Bilateral Brasil-China. *Conjuntura Econômica*, *7*, 62-65.

Vieira Filho, J. E. R., & da Silva, F. P. (2020). *Avaliação de Impacto do Programa de Agricultura de Baixo Carbono no Brasil* (Discussion Paper). Instituto de Pesquisa Econômica Aplicada.

Wake, B. (2021). Fire Fuels Change. *Nature Climate Change*, *4*(8), 662–662.

WorldBank. (2021). *GDP growth (annual %) - China.* Retrieved 2021-10-05, from `https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=CN`

Zhang, P., Zhang, J., & Chen, M. (2017). Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables other than Temperature and Precipitation. *Journal of Environmental Economics and Management*, *83*(C), 8-31.

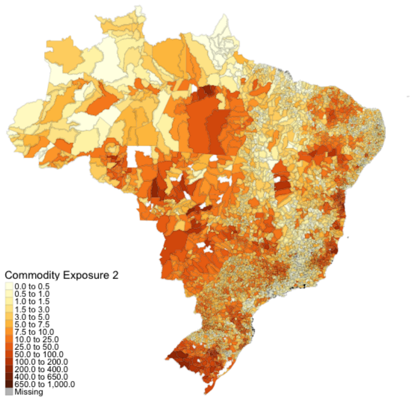
Zivin, J. S. G., Liu, T., Song, Y., Tang, Q., & Zhang, P. (2019). *The Unintended Impacts of Agricultural Fires: Human Capital in China* (Working Paper No. 26205). National Bureau of Economic Research.

Commodity Booms and the Environment

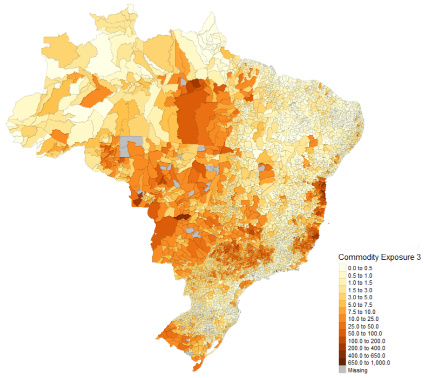
Daniel Da Mata and Mario Dotta

Appendix A Additional Figures and Tables

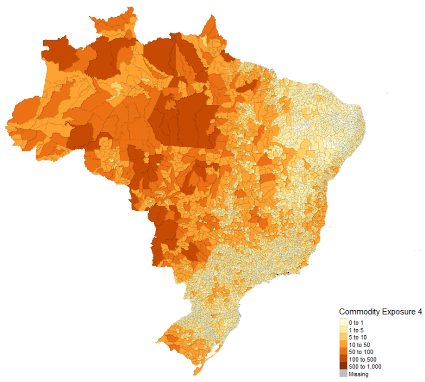
Figure A.1: Alternative Commodity Exposure Indexes



(a) Commodity Exposure 2



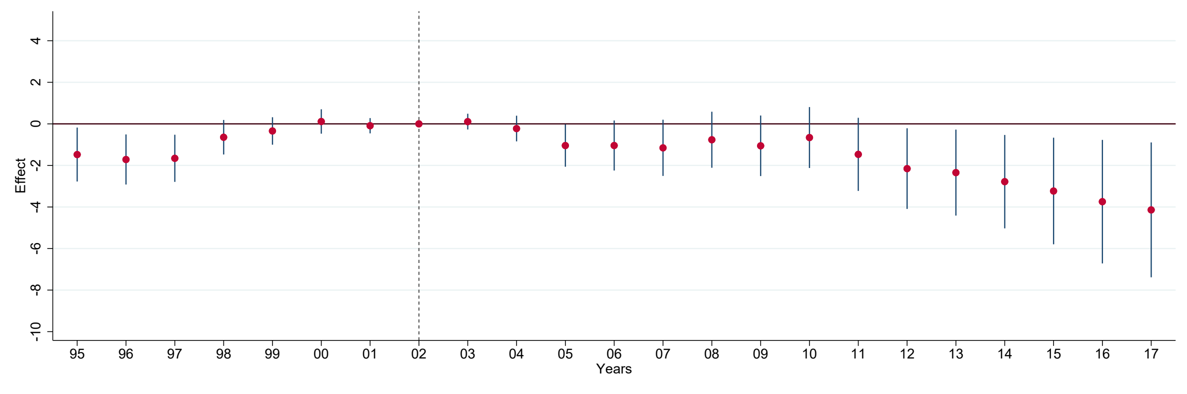
(b) Commodity Exposure 3



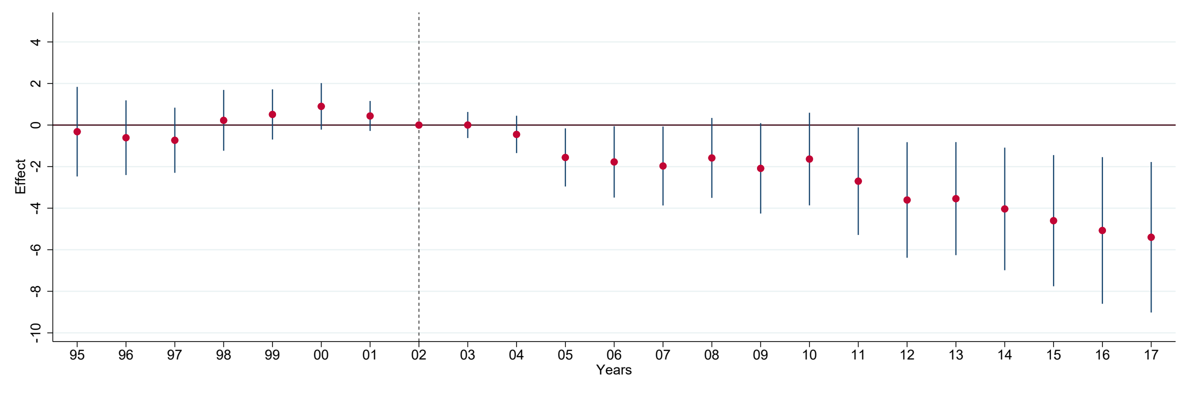
(c) Commodity Exposure 4

Notes: We present three alternative commodity exposure indexes described with further details in Appendix B. Panel (a) shows commodity exposure 2 using pre-boom employment shares as described by Equation (7). Panel (b) displays commodity exposure 3 utilizing pre-period quantity shares following Equation (8). Panel (c) presents commodity exposure 4 which uses land suitability attainable yields from FAO-GAEZ to calculate exposure shares. Following the same pattern as in Figure 1, we select 2010 as reference year.

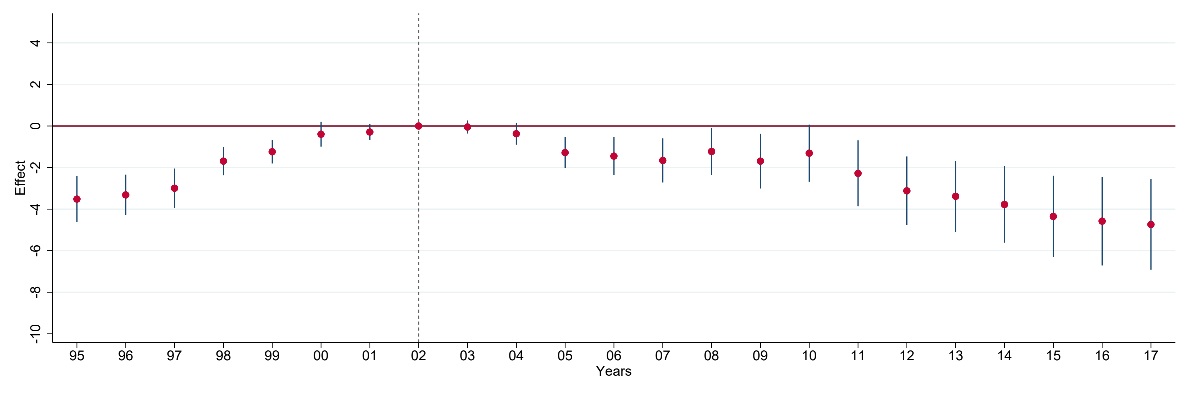
Figure A.2: Parallel Pre-Trends with Rotemberg Weights' Most Relevant Shares — Outcome Variable: Natural Forest Area



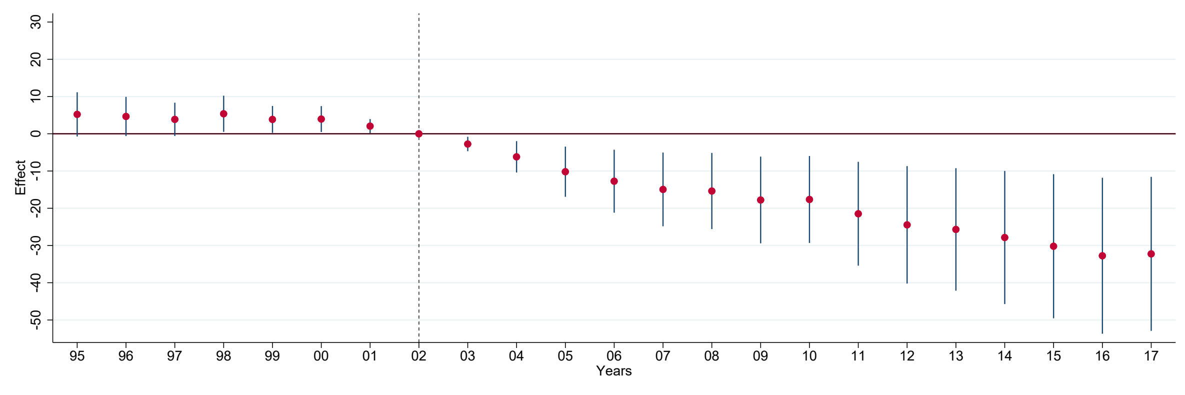
(a) Cocoa Shares



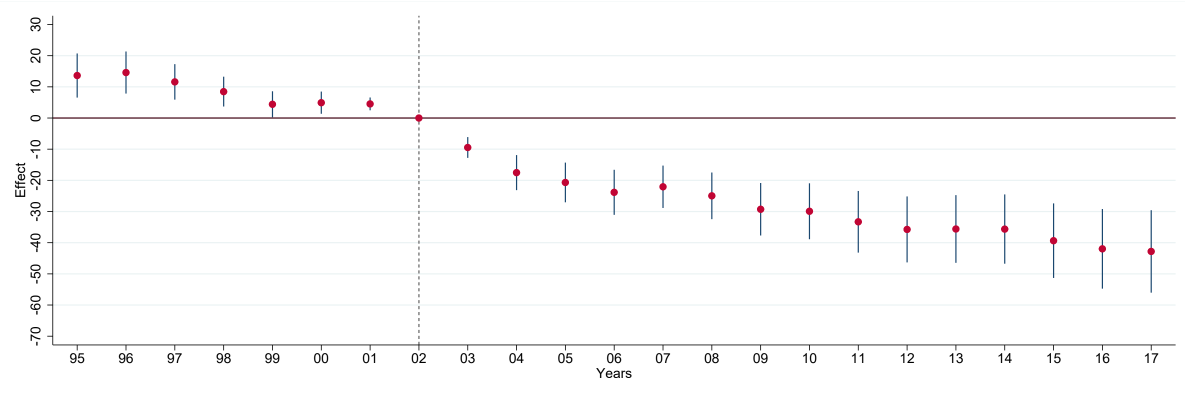
(b) Latex Shares



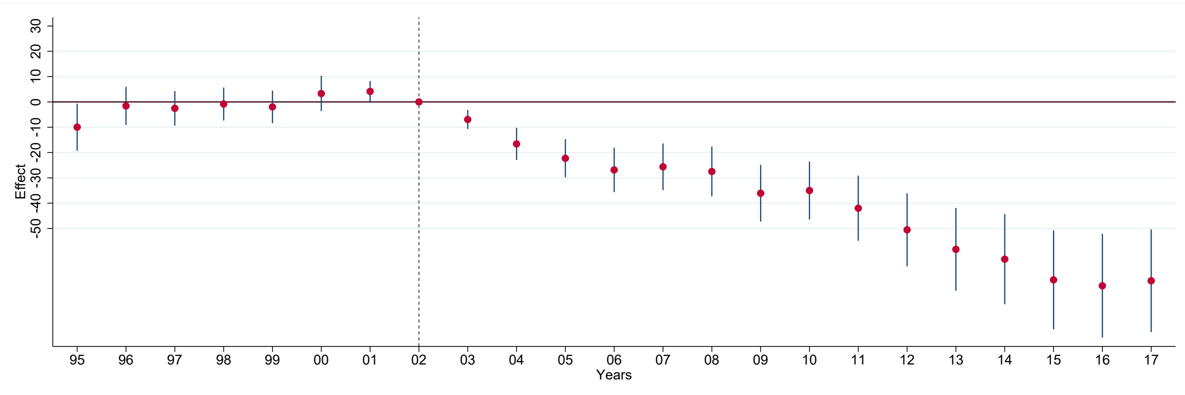
(c) Banana Shares



(d) Bovines Shares



(e) Soybeans Shares



(f) Maize Shares

Notes: Panels (a) through (f) present the results from Equation (4) with standard errors clustered at the municipal level for outcome variable “Natural Forest Area" and shares for “Cocoa", “Latex", “Banana", “Bovines", “Soybeans", and “Maize". We use data on Natural Forest Area (Forest Formation plus Savanna Formation) from MapBiomas at the municipal level. Our specification includes geo-climatic controls, such as rain and temperatures, and socio-economic controls (population, illiteracy, and poverty rates).

Table A.1: Summary Statistics

Statistic	Unit	N	Mean	St. Dev.	Min	Max
Real Local GDP	millions BRL	89,046	695,660.5	7,741,318.0	−19,046	698,952,189
Yearly Deforestation	square Km	29,024	18.0	53.8	0.0	1,808.6
Number of Fires	count	75,336	55.0	209.6	1.0	13,079
Pasture Area	hectares	93,092	30,721.5	65,891.5	0.0	1,648,973.0
Number of Bovines	count	94,639	18,839.5	42,737.1	0.0	1,166,583.0
Crop Area	hectares	94,061	9,836.9	29,911.4	0.0	1,155,466
Lower Emission Crop	hectares	94,061	7,693.8	29,018.7	0.0	1,149,321
GHG Emissions	tons of CO2e	94,690	348,381.5	1,378,533.0	−1,062,874.0	100,047,782.0
GHG Emissions Intensity	tons of CO2e	93,978	117.6	2,571.5	−67,958.7	274,728.7
Net GHG Emissions	tons of CO2e	94,656	261,865.9	1,306,503.0	−15,574,611.0	93,873,249.0
Net GHG Emissions Intensity	tons of CO2e	93,971	84.9	2,758.1	−185,374.4	272,309.6
Real ABC Credit	BRL	27,339	306,196.5	1,269,969.0	0.0	88,123,692.0
No-Tillage Area	hectares	10,181	4,987.2	20,614.8	0.0	547,878
Good Pasture Land	hectares	11,111	12,531.6	42,136.7	0.0	2,093,813
Population	count	94,690	1,794.0	45,611.0	0.0	10,435,546
Average Rain	milimiters	94,010	1,397.0	508.0	201.2	4,043.5
Average Temperature	degrees Celsius	94,010	22.9	3.0	13.7	31.0
Illit. Rate (2001)	percentage	94,690	1.4	6.4	0.0	63.0
Povert. Rate (2001)	percentage	94,690	2.4	11.1	0.0	90.8
Number of Tractors	count	9,546	204.6	304.7	3.0	4,646.0
CE baseline (BRL)	design	94,690	8.6	28.7	0.02	919.0
CE 2 (BRL)	design	93,194	10.6	25.9	0.0	769.2
CE 3 (BRL)	design	93,432	6.2	18.2	0.0	851.5
CE 4 (BRL)	design	94,690	8.7	22.5	0.01	717.7

Notes. This table presents the descriptive statistics of all relevant variables taken into account in the estimations performed in this paper. The analysis period is 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" and "Net GHG Emissions" 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. CE baseline, CE 2, CE 3 and CE 4 represent our baseline exposure, employment share exposure, quantity share exposure, and potential yield exposure, respectively.

Table A.2: Most Relevant Agricultural Products

Commodity	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 "Commodity" for at least one year in 2006 or 2017 and the percent change in the number of producing municipalities in the same period. This table only presents the most relevant agricultural products in Brazil in terms of their contribution to value added and does not include all products taken into account in our baseline commodity exposure specification.

Table A.3: Shift Share Analysis Using Commodity Exposure 2 (Employment Share)

	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

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, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). We use the commodity exposure index from Equation (7) calculated with shares 1996-2000 for years 2001-2017 and with shares 2008-2012 for years 2013-2017. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.4: Shift Share Analysis 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	0.622^{***}	0.610^{***}	0.154^{***}	0.119^{***}	0.246^{***}	0.250^{***}	-3.195^{***}	-3.068^{***}
	(0.068)	(0.067)	(0.032)	(0.032)	(0.028)	(0.028)	(0.430)	(0.430)
Panel B (asinh)								
Commodity Exposure	0.470^{***}	0.454^{***}	0.139^{***}	0.094^{***}	0.129	0.101	-2.728^{***}	-2.737^{***}
	(0.066)	(0.066)	(0.030)	(0.030)	(0.122)	(0.118)	(0.394)	(0.395)
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

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, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). We use the commodity exposure index from Equation (8) calculated with shares 1996-2000 for years 2001-2017 and with shares 2008-2012 for years 2013-2017. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.5: Shift Share Analysis Using Commodity Exposure 4 (FAO-GAEZ Potential Yield)

	Dependent variable:							
	Deforestation		Number of Fires		Net GHG Emissions		ABC Credit	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	0.839^{***}	0.968^{***}	0.520^{***}	0.552^{***}	0.787^{***}	0.834^{***}	-7.432^{***}	-7.792^{***}
	(0.142)	(0.139)	(0.054)	(0.055)	(0.047)	(0.048)	(0.609)	(0.612)
Panel B (asinh)								
Commodity Exposure	-0.654^{***}	-0.539^{***}	0.449^{***}	0.466^{***}	0.597^{***}	0.792^{***}	-8.062^{***}	-8.288^{***}
	(0.169)	(0.165)	(0.056)	(0.057)	(0.181)	(0.189)	(0.559)	(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 (Panel A)	29,024	28,429	75,336	74,704	90,873	90,575	27,339	27,163
Observations (Panel B)	29,024	28,429	75,336	74,704	94,656	93,993	27,339	27,163

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, poverty rate, and illiteracy rate. Weather Controls utilize geo-climatic data (rainfall and temperatures). We use the commodity exposure index from Equation (8) calculated with shares given by the potetial yields from FAO-GAEZ. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.6: 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	0.8273 (n.obs: 182)	*EHW*	0.1136750	3.388401e-13	0.6045243	1.050122
		AKM	0.2188124	1.562184e-04	0.3984588	1.256188
		AKM0	Inf	0.1405616	-Inf	Inf)
Number of Fires	0.40626 (n.obs: 990)	*EHW*	0.03478513	0.00000000	0.33808049	0.47443573
		AKM	0.23419128	0.08278906	-0.05274839	0.8652646
		AKM0	0.38370943	0.23397616	-0.72573517	0.7783782
Net GHG Emissions	0.28997 (n.obs: 2,430)	*EHW*	0.02068598	0.0000000000	0.24942186	0.3305094
		AKM	0.08164061	0.0003827033	0.12995297	0.4499783
		AKM0	0.09885165	0.0169517943	0.08484193	0.4723333

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 perform that for dependent variables "Deforestation", "Number of Fires", and "Net GHG Emissions". 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 (ii) 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 $2_{z_{1-\alpha/2}}$). We used the "ShiftShareSE" package in R to estimate these results. In order to find the results for "Deforestation", we had to drop the barley share in the weight matrix due to collinearity in the share matrix—following Michael Kolesár (2020).

Table A.7: Inference Assessment by Ferman (2021)

Dependent Variable	Commodity Exposure	Assessment (5% test)
	(i)	(ii)
Deforestation	0.9952	0.04125
Number of Fires	0.5685	0.06125
Net GHG Emissions	0.8794	0.05000

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 Equation (2). In column (ii) we show the assessment-five-percent-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 Stata code to run this assessment.

Table A.8: 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	0.780	0.798	0.411	0.437	0.310	0.310	-4.56	-4.71
	(0.183)***	(0.186)***	(0.0732)***	(0.0758)***	(0.0615)***	(0.0616)***	(0.602)***	(0.604)***
	[0.280]**	[0.286]**	[0.112]*	[0.117]	[0.105]**	[0.105]**	[0.717]***	[0.736]***
Panel B (asinh)								
Commodity Exposure	0.471	0.472	0.379	0.399	0.548	0.461	-4.15	-4.33
	(0.178)**	(0.178)**	(0.0700)***	(0.0741)***	(0.164)***	(0.157)**	(0.544)***	(0.550)***
	[0.264]*	[0.269]*	[0.104]***	[0.113]***	[0.235]**	[0.211]**	[0.649]***	[0.676]***
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	29,024	28,429	75,336	74,704	94,656	93,993	27,339	27,163

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, with 510 units and 133 units, respectively. Initial controls have time-varying coefficients, and include variables such as population size, 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.9: Multiple Hypothesis Testing Correction

Description	Dependent Variable	Coefficient	P-Value	Multiple Hypothesis Test — Corrected P-Value
	(i)	(ii)	(iii)	(iv)
Figure 2	Local GDP	0.0982***	0.00000000	0.00000000
	Deforestation	0.7979***	0.00000000	0.00000000
	Number of Fires	0.4365***	0.00000000	0.00000000
Figure 3	Pasture Land	0.1110***	0.00000048	0.00000096
	Heads/Hectare	−0.1811***	0.00000000	0.00000000
	Crop/Hectare	0.1202***	0.00000975	0.00000975
	Lower Em. Crops	−0.6989***	0.00000000	0.00000000
Figure 4	Gross GHG Emissions	0.3188***	0.00000000	0.00000000
	GHG Intensity Emissions	0.4029***	0.00000000	0.00000000
	Net GHG Emissions	0.3085***	0.00000000	0.00000000
	Net GHG Intensity Emissions	0.4154***	0.00000000	0.00000000
Figure 5	% ABC Credit	−0.1614***	0.00000000	0.00000000
	% No-Till Area	−0.0074	0.10600000	0.10600000
	% Well-Managed Pastureland	−0.0598***	0.00000000	0.00000000
	Net GHG Emissions	0.0640*	0.04784435	0.09568870

Notes. This table presents the results of multiple hypothesis testing following Holm (1979), as described in Subsection 5.6. We consider outcomes within each Subsection 5.1–5.4 as a separate "family" (e.g., outcomes in Subsection 5.1 are considered one family of outcomes; and outcomes in Subsection 5.2 are considered another family). Within each family, the most significant hypothesis is rejected if the associated p-value is lower than α/S, which is equivalent to a Bonferroni correction. This is equivalent to multiplying the p-value by S. The second most significant hypothesis is rejected if the associated p-value is lower than $\alpha/(S-1)$. This is equivalent to multiplying the p-value by $S-1$. Finally, the jth most significant hypothesis is rejected if the associated p-value is lower than $\alpha/(S-j+1)$. This stepwise procedure stops if a hypothesis is not rejected. 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, considering p-values in column (iv).

Table A.10: Shift-Share analysis using data for 2001–2004

	Dependent variable:					
	Deforestation		Number of Fires		Net GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure	-0.215	0.383	0.547^{***}	1.256^{***}	-0.042	0.048
	(0.253)	(0.248)	(0.144)	(0.142)	(0.054)	(0.059)
Panel B (asinh)						
Commodity Exposure	-0.418	0.228	0.247^{*}	0.955^{***}	-0.669^{***}	-0.482^{**}
	(0.272)	(0.264)	(0.147)	(0.144)	(0.197)	(0.204)
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 (Panel A)	7,094	6,954	17,869	17,719	21,668	21,581
Observations (Panel B)	7,094	6,954	17,869	17,719	22,272	22,116

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, 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: Rotemberg Weights following Goldsmith-Pinkham et al. (2020)

Crops and Livestock	**RWs**
Cocoa	0.1696
Latex	0.1693
Banana	0.1362
Orange	0.0926
Bovines	0.0739
Rice	0.0731
Groundnut	0.044
Sugar	0.0414
Tobacco	0.0393
Soybeans	0.0351
Maize	0.0320
Wheat	0.0302
Coffee	0.0286
Barley	0.0218
Sorghum	0.0123

Notes. This table presents the Rotemberg Weights estimated as described in Subsection 5.6 and online Appendix B.

Table A.12: Test 1: Correlates of 2013 shares

	Dependent variable:								
	Main outcome variables			Most relevant commodity shares					
	Deforestation	Number of Fires	GHG Emissions	Bovines	Soybeans	Maize	Latex	Cocoa	Banana
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Commodity Exposure	0.691***	0.659***	0.813***						
	(0.026)	(0.019)	(0.014)						
Population	−0.00000**	0.00000	0.00000***	0.000	0.000	0.000*	0.000	0.000	0.000
	(0.00000)	(0.00000)	(0.00000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Rain	−0.001***	0.0004***	0.0003***	0.00000***	0.00000***	0.000	0.00000***	0.00000***	0.00000***
	(0.0001)	(0.00004)	(0.00003)	(0.00000)	(0.00000)	(0.000)	(0.00000)	(0.00000)	(0.00000)
Average Temperature	0.154***	0.188***	0.153***	0.0001***	0.00001***	0.00001***	0.0001***	0.0001***	0.0001***
	(0.017)	(0.007)	(0.005)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
Illiteracy	−0.019***	−0.015***	−0.019***	0.00000*	−0.00000**	−0.00000***	0.00002***	0.00003***	0.00002***
	(0.004)	(0.003)	(0.002)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Poverty	0.009***	0.014***	−0.007***	−0.00000***	−0.00000***	0.00000***	−0.00001***	−0.00001***	−0.00000***
	(0.002)	(0.002)	(0.001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	1,663	4,024	5,521	5,530	5,530	5,530	5,530	5,530	5,530
R^2	0.339	0.450	0.543	0.112	0.047	0.010	0.064	0.059	0.123
Adjusted R^2	0.337	0.449	0.542	0.111	0.046	0.009	0.063	0.058	0.122

Notes. This table presents our correlates test following Goldsmith-Pinkham et al. (2020). Each column reports an OLS regression for year 2013. Columns (i) through (iii) present the cross-section results of our main specification from Equation (1) for our main outcome variables “Deforestation", “Number of Variables", and “GHG Emissions". In columns (iv) through (ix) we report the results of our baseline controls on some of the most relevant shares given by the Rotemberg Weights in Table A.11 plus bovines, soybeans and maize.

Table A.13: Poisson Estimates for the Number of Fires

	Dependent variable:	
	Number of Fires	
	(i)	(ii)
Panel A (log)		
Commodity Exposure	0.0864***	0.0920***
	(0.0150)	(0.0153)
Panel B (asinh)		
Commodity Exposure	0.0921***	0.0959***
	(0.0130)	(0.0132)
Initial Controls	No	Yes
Weather Controls	No	Yes
Municipality	Yes	Yes
Observations (Panel A and B)	75,336	74,704

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, 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.14: 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	1.053***	1.017***	0.456***	0.656***	0.695***	0.659***
	(0.185)	(0.186)	(0.095)	(0.101)	(0.062)	(0.069)
Panel B (asinh)						
Commodity Exposure	0.803***	0.775***	0.398***	0.581***	2.043***	1.792***
	(0.200)	(0.203)	(0.100)	(0.107)	(0.335)	(0.356)
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 (Panel A)	3,484	3,414	9,070	8,994	10,747	10,708
Observations (Panel B)	3,484	3,414	9,070	8,994	11,136	11,058

Notes. This table presents results from estimation of Equation (6) 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, poverty rate, and illiteracy rate. Weather controls utilize geo-climatic variables (temperature and rainfall). We use the commodity exposure index from Equation (8). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.15: Removing One Commodity at a Time — Most Relevant Commodities

	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	0.720^{***}	0.743^{***}	0.407^{***}	0.436^{***}	0.311^{***}	0.309^{***}	-4.655^{***}	-4.817^{***}
	(0.085)	(0.087)	(0.036)	(0.036)	(0.030)	(0.030)	(0.496)	(0.497)
Panel 2								
Commodity Exposure - without maize	0.762^{***}	0.784^{***}	0.383^{***}	0.403^{***}	0.301^{***}	0.299^{***}	-4.519^{***}	-4.661^{***}
	(0.087)	(0.088)	(0.036)	(0.037)	(0.030)	(0.030)	(0.501)	(0.501)
Panel 3								
Commodity Exposure - without sugar	0.810^{***}	0.830^{***}	0.425^{***}	0.447^{***}	0.315^{***}	0.313^{***}	-4.346^{***}	-4.502^{***}
	(0.087)	(0.088)	(0.036)	(0.037)	(0.030)	(0.030)	(0.503)	(0.503)
Panel 4								
Commodity Exposure - without rice	0.683^{***}	0.699^{***}	0.432^{***}	0.452^{***}	0.324^{***}	0.321^{***}	-4.389^{***}	-4.507^{***}
	(0.082)	(0.083)	(0.035)	(0.036)	(0.030)	(0.030)	(0.499)	(0.499)
Panel 5								
Commodity Exposure - without banana	0.683^{***}	0.713^{***}	0.414^{***}	0.435^{***}	0.306^{***}	0.305^{***}	-4.712^{***}	-4.841^{***}
	(0.086)	(0.088)	(0.036)	(0.037)	(0.030)	(0.030)	(0.505)	(0.505)
Panel 6								
Commodity Exposure - without orange	0.648^{***}	0.670^{***}	0.443^{***}	0.460^{***}	0.277^{***}	0.274^{***}	-4.288^{***}	-4.448^{***}
	(0.085)	(0.086)	(0.035)	(0.036)	(0.029)	(0.029)	(0.499)	(0.499)
Panel 7								
Commodity Exposure - without coffee	0.712^{***}	0.753^{***}	0.286^{***}	0.294^{***}	0.377^{***}	0.387^{***}	-2.366^{***}	-2.095^{***}
	(0.087)	(0.088)	(0.037)	(0.037)	(0.031)	(0.031)	(0.555)	(0.560)
Panel 8								
Commodity Exposure - without cocoa	0.760^{***}	0.770^{***}	0.326^{***}	0.362^{***}	0.258^{***}	0.254^{***}	-4.676^{***}	-4.793^{***}
	(0.090)	(0.092)	(0.036)	(0.037)	(0.031)	(0.031)	(0.527)	(0.529)
Panel 9								
Commodity Exposure - without bovines	0.728^{***}	0.769^{***}	0.253^{***}	0.267^{***}	0.190^{***}	0.198^{***}	-4.276^{***}	-4.490^{***}
	(0.082)	(0.084)	(0.033)	(0.033)	(0.026)	(0.026)	(0.419)	(0.421)
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 (Panels 1-9)	29,024	28,429	75,336	74,704	90,873	90,575	27,339	27,163

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. We use the commodity exposure index from Equation (2), but we remove one commodity for each of the Panels 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. We do not take into account in this calculation all commodities used to estimate the commodity exposure index of Equation (2), and we only consider the most relevant commodities. 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, 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.16: 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	−0.031	0.093	-0.191^{***}	-0.198^{***}	−0.936	−1.099
	(0.088)	(0.088)	(0.063)	(0.063)	(0.070)	(0.070)	(0.934)	(0.945)
Panel B (asinh)								
Commodity Exposure	−0.006	−0.002	−0.051	0.062	0.115	0.125	−0.968	−1.106
	(0.089)	(0.089)	(0.059)	(0.059)	(0.257)	(0.259)	(0.829)	(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 (Panel A)	5,726	5,609	16,113	15,992	18,765	18,722	7,275	7,228
Observations (Panel B)	5,726	5,609	16,113	15,992	19,331	19,201	7,275	7,228

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

	Dependent variable:					
	Local GDP		Deforestation		Number of Fires	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Panel A (log)						
Commodity Exposure	0.0999***	0.0983***	0.7796***	0.7979***	0.4107***	0.4365***
	(0.0134)	(0.0134)	(0.0874)	(0.0892)	(0.0364)	(0.0370)
Panel B (asinh)						
Commodity Exposure	0.0907***	0.0876***	0.4706***	0.4723***	0.3785***	0.3990***
	(0.0135)	(0.0135)	(0.0869)	(0.0873)	(0.0364)	(0.0371)
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	89,045	88,405	29,024	28,429	75,336	74,704

Notes. This table presents results from estimation of Equation (1) for dependent variables “Local GDP", “Deforestation" and “Number of Fires" from 2001-2017. Variable “Local GDP" is the value for gross domestic product at the local level measured in 2010 Brazilian *reais*, “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, 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.18: Effects of Commodity Booms: Land Allocation, Crop Mix, and Productivity

	Dependent variable:			
	Pasture Land	Heads Per Hectare	Crop Prod. Hectare	Lower Emission Crop Land
	(i)	(ii)	(iii)	(iv)
Panel A (log)				
Commodity Exposure	0.1110^{***}	-0.1812^{***}	0.1203^{***}	-0.7042^{***}
	(0.0220)	(0.0158)	(0.0272)	(0.0504)
Panel B (asinh)				
Commodity Exposure	0.1159^{***}	-0.2106^{***}	0.0997^{***}	-0.5666^{***}
	(0.0196)	(0.0168)	(0.0274)	(0.0440)
Initial Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes
Observations	92,480	92,413	91,929	93,398

Notes. This table presents results from estimation of Equation (1) for dependent variables "Pasture Land", "Heads Per Hectare", "Crop Prod. Hectare", and "Lower Emission Crop Land" for Brazilian municipalities using data from years 2001 and 2017. Column (i) presents the change in allocation of land towards pastureland. Columns (ii) and (iii) present productivity measures, showing heads of cattle livestock per hectare and crop-productivity per hectare measured as tons of produce per hectare. Column (iv) 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 as total land used by lower-emission crops. In Panel A, dependent variables and the commodity exposure variable 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, 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: Greenhouse Gas Emissions

	Dependent variable:			
	GHG Emissions Whole Economy	GHG Emissions Intensity	Net GHG Emissions Whole Economy	Net GHG Emissions Intensity
	(i)	(ii)	(iii)	(iv)
Panel A (log)				
Commodity Exposure	0.3188***	0.4029***	0.3086***	0.4155***
	(0.0222)	(0.0273)	(0.0304)	(0.0321)
Panel B (asinh)				
Commodity Exposure	0.2083***	0.2840***	0.4873***	0.3415***
	(0.0443)	(0.0303)	(0.1221)	(0.0386)
Initial Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Municipality & Time FE	Yes	Yes	Yes	Yes
Observations (Panel A)	93,928	91,849	90,575	89,297
Observations (Panel B)	94,010	91,919	93,993	91,919

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 Intensity" emissions (gross), “Net GHG Emissions" for the whole economy, and “Net GHG Intensity" emissions. 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, 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: adherence to a Climate Mitigation Policy

	Dependent variable:							
	% ABC Credit		% No-Till Area		% Well-Managed Pastureland		GHG Emissions	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Panel A (log)								
Commodity Exposure	-0.2095^{***}	-0.1614^{***}	0.0422^{***}	-0.00754^{***}	-0.0766	-0.0599^{***}	0.0954^{***}	0.0640^{**}
	(0.0189)	(0.0202)	(0.0046)	(0.0046)	(0.0045)	(0.0048)	(0.0302)	(0.0324)
Panel B (asinh)								
Commodity Exposure	-0.1666^{***}	-0.1185^{***}	0.0380^{***}	-0.0060	-0.0678^{***}	-0.0547	0.0176	0.0017
	(0.0161)	(0.0172)	(0.0039)	(0.0038)	(0.0037)	(0.0040)	(0.0377)	(0.0317)
Initial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	Yes	Yes	No	Yes
Municipality & Time FE	Yes	Yes	No	No	No	No	Yes	Yes
Observations (Panel A)	27,038	26,868	5,438	5,402	5,520	5,480	27,794	27,594
Observations (Panel B)	27,038	26,868	5,438	5,402	5,520	5,480	27,850	27,650

Notes. This table presents results from estimation of Equation (1) for dependent variables "% ABC Credit", "% No-Till Area", "% Well Managed pastureland", and "Net GHG Emissions" from 2013-2017 for Brazilian municipalities. Columns (i) through (vi) are measured in percentage, and columns (vii) and (viii) are measured in tons of CO2eq. Columns (iii) through (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 municipalities and time. In Panel A, the dependent variables for columns (vii) and (viii) and the commodity exposure index are transformed into $log+1$, apart from columns (i) through (vi) in which we use the dependent variables in percentage. In Panel B, we follow the same pattern but instead of using the logarithmic transformation we utilize 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, 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.21: 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	0.936***	1.036***	0.622***	0.674***	0.725***	0.743***	0.423***	0.578***	0.386***	0.402***	0.659***	0.597***
	(0.118)	(0.115)	(0.081)	(0.082)	(0.087)	(0.087)	(0.142)	(0.154)	(0.105)	(0.106)	(0.152)	(0.149)
Panel B (asinh)												
Commodity Exposure	0.529***	0.677***	0.571***	0.622***	1.583***	1.546***	0.104	0.149	0.426***	0.443***	1.749**	1.182
	(0.109)	(0.107)	(0.078)	(0.080)	(0.312)	(0.304)	(0.154)	(0.162)	(0.106)	(0.106)	(0.840)	(0.791)
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)	20,491	20,491	22,743	22,743	23,624	23,624	9,467	8,872	9,399	8,804	7,696	7,466
Observations (Panel B)	20,491	20,491	22,743	22,743	24,378	24,378	9,467	8,872	9,399	8,804	9,486	8,891

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, 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.22: 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)	1.108***		0.395***		0.885***	
	(0.075)		(0.040)		(0.044)	
Commodity Exposure (crops)		0.769***		0.267***		0.198***
		(0.084)		(0.033)		(0.026)
Panel B (asinh)						
Commodity Exposure (beef)	0.842***		0.303***		1.463***	
	(0.071)		(0.034)		(0.190)	
Commodity Exposure (crops)		0.625***		0.230***		0.415***
		(0.083)		(0.033)		(0.107)
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)	28,429	28,429	74,704	74,704	90,575	90,575
Observations (Panel B)	28,429	28,429	74,704	74,704	93,993	93,993

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, 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.23: 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	1.144***	1.160***	0.395***	0.434***	0.376***	0.365***	−0.469***	−0.485***
	(0.092)	(0.094)	(0.029)	(0.030)	(0.033)	(0.033)	(0.072)	(0.073)
Panel B								
log(y) for y>1; y, for 0<y<1								
dummy = 1 for y<1								
Commodity Exposure	1.107***	1.123***	0.389***	0.426***	0.376***	0.365***	−0.469***	−0.485***
	(0.092)	(0.094)	(0.028)	(0.029)	(0.033)	(0.033)	(0.072)	(0.073)
Panel C								
dummy= 1 for y>0								
Commodity Exposure	0.829***	0.848***	0.382***	0.418***	0.314***	0.310***	−0.469***	−0.485***
	(0.087)	(0.089)	(0.027)	(0.028)	(0.022)	(0.022)	(0.072)	(0.073)
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 and B)	29,024	28,429	94,690	94,010	94,690	94,010	27,339	27,163
Observations (Panel C)	29,024	28,429	94,690	94,010	94,608	93,928	27,339	27,163

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, 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.24: 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	0.897***	0.869***	0.351***	0.417***	0.413***	0.400***	−2.667*	−3.275**
	(0.210)	(0.212)	(0.085)	(0.086)	(0.092)	(0.092)	(1.488)	(1.513)
Panel B (asinh)								
Commodity Exposure	0.554***	0.510**	0.295***	0.366***	0.606	0.313	−2.614*	−3.268**
	(0.206)	(0.204)	(0.083)	(0.084)	(0.448)	(0.430)	(1.505)	(1.533)
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 (Panels A)	3,763	3,644	8,619	8,500	8,296	8,255	2,548	2,513
Observations (Panel B)	3,763	3,644	8,619	8,500	8,670	8,551	2,548	2,513

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 of observation. Standard errors are also clustered at the micro-region level. Initial controls have time-varying coefficients, and include variables such as population size, 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.25: 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	0.369***	0.343***	0.216***	0.228***	0.220***	0.216***	−2.606***	−2.559***
	(0.032)	(0.032)	(0.039)	(0.039)	(0.032)	(0.032)	(0.139)	(0.139)
Panel B (asinh)								
Commodity Exposure	0.398***	0.370***	0.192***	0.201***	0.940***	0.890***	−2.740***	−2.682***
	(0.035)	(0.036)	(0.046)	(0.046)	(0.187)	(0.185)	(0.142)	(0.143)
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)	72,539	72,539	72,539	72,539	69,776	69,776	72,539	72,539
Observations (Panel B)	72,539	72,539	72,539	72,539	72,539	72,539	72,539	72,539

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 MCAs (AMCs) for year 2000 — Minimum Comparable Areas, or *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, poverty rate, and illiteracy rate. Weather controls include geo-climatic variables (rainfall and temperature). We use the commodity exposure index from Equation (8). Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01.

Table A.26: 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	0.00002***	0.00002***	0.00005***	0.0001***	1.174***	1.253***	−0.647*	−0.801*
	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.245)	(0.288)	(0.379)	(0.447)
Panel B (asinh)								
Commodity Exposure	0.00002***	0.00002***	0.00005***	0.0001***	1.174***	1.253***	−0.647*	−0.801*
	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.245)	(0.288)	(0.379)	(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	28,628	28,033	74,572	73,940	93,585	92,922	27,037	26,861

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 initial 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, 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.27: 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	0.00000***	0.00000***	0.00002***	0.00002***	5.852	6.990	0.004	0.003
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(4.493)	(5.353)	(0.003)	(0.003)
Panel B (asinh)								
Commodity Exposure	0.00000***	0.00000***	0.00002***	0.00002***	5.852	6.686	0.004	0.003
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(4.493)	(5.150)	(0.003)	(0.003)
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	28,931	28,336	94,690	94,010	94,690	94,010	94,690	94,010

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 initial 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, 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.

Appendix B Detailing the Robustness and Specification Checks

We now describe all the tables, figures, and results presented in Appendix A. We first show Table A.1, which displays the summary statistics of all variables taken into consideration in our dataset. Columns “Statistic" and “Unit" describe the variable and its unit of measurement, respectively, while column “N" shows the number of observations and the remaining columns present basic statistics. The last four lines in this table show the commodity exposure indexes (CE) we utilize in our estimations and robustness checks described below: CE baseline, CE 2, CE 3, and CE 4 represent our baseline exposure, employment share exposure, quantity share exposure, and potential yield exposure, respectively. Table A.2 presents the number of municipalities in Brazil that produce each of the agricultural commodities in column “Commodity"—this is relevant to demonstrate the amplitude of our empirical strategy since all those commodities are included in our commodity exposure index, and they represent a relevant share of gross agricultural production. For a better sense of the alternative commodity exposure indexes explained in Section 3, we plot their exposure maps for the base year 2010, when commodity prices were at a high point in the super-cycle—see Figure A.1. Notice that alternative definitions for commodity exposure indexes seem to be correlated.

We then present Tables A.3 through A.27 with our robustness checks and additional results. We begin with Tables A.3 through A.5, showing results for the alternative commodity exposure measures mentioned above (which we detail 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.6. 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.7. 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.8. Finally, we run a multiple hypothesis tests; results are in Table A.9.

Next, we run a sensitivity test for a period in which the commodity boom had not yet reached sustainable levels—shown in Table A.10. We then estimate the Rotemberg Weights for all the commodities used in our baseline commodity index to evaluate the share exogeneity assumption. We utilize a cross-section approach, using year 2013. Weights are shown in Table A.11. We calculate the weights as follows:

$$\hat{\alpha}_k = \frac{P_k CE_i q_{ik}}{\sum_k P_k CE_i q_{ik}} \tag{5}$$

where α_k is the RW for crop/livestock k, P_k are prices for crop/livestock k, CE_i is the commodity exposure index estimated according to Equation (2) for municipality i, and q_{ik} is the share of commodity k for municipality i—see Section 3. We then test whether covariates influence our baseline results and run a pre-trend analysis for the most relevant shares—results are displayed in Table A.12 and Figure A.2, respectively.

Additionally, in Table A.13 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.14 in which we demonstrate a first difference approach to our main dependent variables following:

$$\Delta y_i = \beta \Delta CE_i + \gamma \Delta X_i + \eta \Delta W_i + \varepsilon_i \tag{6}$$

where we follow the same specification as in Equation (1) but only for the years 2013 and 2003—a year of considerably high prices for agricultural commodities and the beginning of the commodity cycle, respectively. In Table A.15 we run our baseline commodity exposure index on our main dependent variables removing the most relevant commodities from the index, one at a time. We then run a relevant placebo test. 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 tax collection as shares in a new commodity exposure index calculated following Equation (2) using iron ore international prices from the World Bank Pink Sheet in *reais* as shifts. Importantly, iron ore represents more than 75% of Brazil's mining production and about 70% of all mineral extraction takes place in 10 municipalities—all of which are iron ore producers. We display the results in Table A.16. Subsequently, we present Tables A.17 through A.22 which give detailed results for Figures 2 through 7, respectively. In these tables, we show coefficients for $log + 1$ and $asinh$ (the hyperbolic inverse sine transformation), and we also present controls, the number of observations, and whether estimations had fixed effects.

We then check for different log specifications in Table A.23. We first apply *log* and *log+1* on variable values greater than 1 and on interval [0, 1], respectively. We add a dummy for the latter variable as control for Equation (1) (see Panel A). Secondly, we apply *log+1* on variable values $\in$ [0, 1] and use actual values otherwise, using the same dummy as above as control (see Panel B). Finally, we test our original specification with dummies for dependent variable values greater than 0 (see Panel C).

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.24. We also perform an exercise with MCAs—*Áreas Minimamente Comparáveis*—in Table A.25. Finally, we switch our dependent variables to the per capita level in Table A.26 and to the per hectare level in Table A.27. It is worth mentioning that our results remain largely valid after all the described robustness checks.

Below, we describe the alternative commodity exposure indexes used in the robustness exercises of our main specification given by Equation (1)—the results given in Tables A.3 through A.5. First, we perform an estimation following Benguria et al. (2021) by defining 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:

$$p_{rt} = \frac{\sum_{c \in C} p_{ct} e_{cr}}{\sum_{c \in C} e_{cr}} \tag{7}$$

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 (agricultural census year). 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 categories: temporary crops, permanent crops, and livestock. We define sugar-cane, 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 (7). Table A.3 shows our results for this specification. All our previous results remain significant.

As for alternative exposure 3, we define the variable CE_{it} for municipality i and time t according to the following equation:

$$CE_{it} = \sum_{k} q_{ki,T} P_{kt} \tag{8}$$

where the term $q_{ki,T}$ is the share of total production (in tons) for crop or livestock k from years $(T-5)$ to 2000 or 2012 in municipality i—given by the quantities from IBGE's PAM and PPM—, which sums up to 1 across crop or livestock k, and P_{kt} represents the real international commodity prices for crop or livestock k at time t converted into Brazilian 2010 *reais* according to Brazil's official real exchange rate data.

For commodity exposure 4, we perform a similar procedure as above, but instead of utilizing quantities to calculate a lagged share to be used in Equation (8) above, we use FAO-GAEZ's land suitability attainable yield directly to calculate the shares. This yields a direct measure of GAEZ's suitability. Tables A.3 and A.4 show our results for these specifications. All our previous results remain largely robust.