The dynamics of cattle expansion and deforestation in the Brazilian Amazon *

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Abstract

Demand for agricultural products is a major driver of deforestation in the Brazilian Amazon. However, it is well known that newly deforested land is relatively unproductive, and agricultural products are barred from the predominant agriculture supply chains. An alternative, intermediate channel is the appropriation of unclaimed public land, where forest is cut and agricultural activity feigned to justify claims of ownership. In this paper, we identify the deforestation impacts of expanding agricultural production, differentiating it from other channels with different implications for economic and environmental policy. We use a shift-share design, exploiting international changes in beef consumption and geo-referenced locations of slaughterhouses, to identify causal effects, and find that pasture and cattle herd expansions are major drivers of deforestation. We also find that these impacts diminished in recent years, indicating that other factors, such as land appropriation motives, have become relatively more important. Our findings suggest that agricultural intensification could help decrease land pressure, and highlight the growing deforestation impacts of an ongoing expansion of infrastructure and legalization of land claims in the Brazilian Amazon.

Keywords: agricultural demand, shift-share design, deforestation, causal effect

JEL Classification: Q15, O13, C36, Q23

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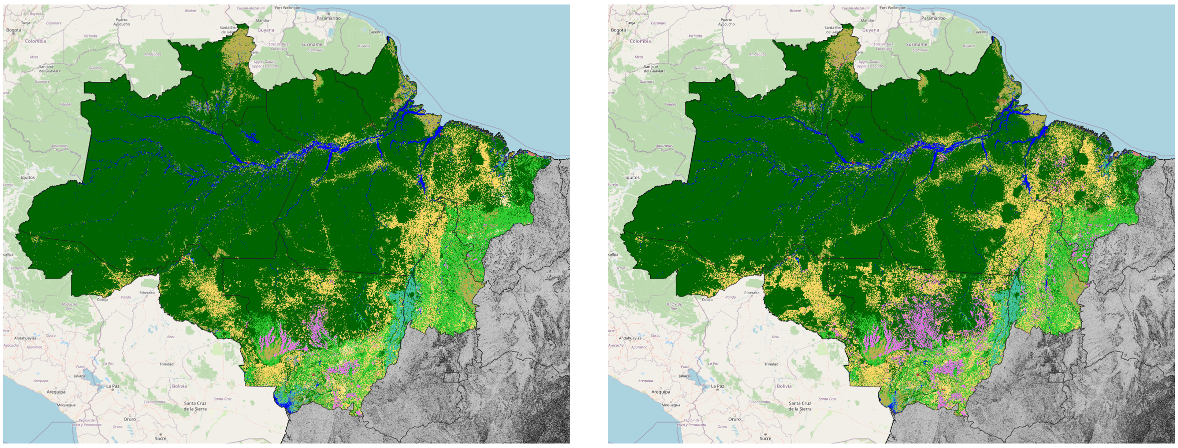
1 Introduction

Deforestation in the Brazilian Amazon is on the rise again. After successfully reigning in deforestation rates in the years 2003–2011 and a stagnation until roughly 2018, they have increased sharply in the years thereafter. Similarly, other endangered biomes such as the Cerrado, the world's most biodiverse savanna, have come under pressure. Effectively tackling biodiversity loss, climate change and the destruction of livelihoods requires swift and decisive actions, involving policies that target the main drivers of deforestation accurately. There are multiple dimensions to which this over-exploitation can be attributed: weakening of environmental legislation (Garrett et al., 2021), declines in the enforcement capacities of environmental policy agencies (Kuschnig et al., 2023), and the generally anti-environmental rhetoric of some of the more recent government administrations (Oliveira et al., 2023). While these institutional factors play an important role, one of the key aspects is the clearing of forest and other vegetation for agricultural uses.

In Brazil, large swaths of areas in the Amazon and other endangered biomes are deforested to be used as cattle pasture or soybean plantations (c.f. Figure 1). The expansion of cattle pasture has been identified to be the *proximate* cause of around 70% of total deforestation in the Brazilian Amazon in recent years (MapBiomas, 2023), much of which occurs illegally (Rajão et al., 2020). It has also been a major driver of vegetation loss in the Cerrado biome, in which more than half of the area is now used for agricultural purposes, with cattle pasture being the dominant land use type by now (MapBiomas, 2023). In recent years however, the centre of the Brazilian beef industry has continuously moved northwards and shifted into the Amazon (Vale et al., 2022). The conversion of pristine forest to pasture and subsequent beef production, or other agricultural purposes, has disastrous environmental consequences. Besides dramatic impacts on local biodiversity (Gibson et al., 2011), changes in regional climatic conditions (Leite-Filho et al., 2021), and the adverse effects on the livelihoods of indigenous people (Villén-Pérez et al., 2022), these land use changes are a major source of greenhouse gas emissions (Houghton et al., 2012), adding a global dimension to the problem. The Brazilian beef industry alone causes up to a fifth of all commodity-driven emissions from the tropics worldwide (Pendrill et al., 2019), at a scale comparable to total emissions of major polluters such as South Africa. With most of Brazil's commitments for reducing greenhouse gas emissions relying on curbing deforestation (Rochedo et al., 2018), the agricultural sector and related land use changes play an immense role in achieving these goals.

There are multiple motives behind the agricultural expansion and accompanying deforestation in tropical rainforests. Rising demand for agricultural products, both domestically and in emerging countries, is a crucial factor for the expansion of agricultural production (Cusack et al., 2021). Changes towards a more meat-oriented diet, especially



2000 2020

Figure 1: Land cover in the Legal Amazon in 2000 and 2020, with pristine forest formation in dark green, savanna formation in light green, pasture in yellow, and croplands in purple. Source: MapBiomas (2023)

beef products, in emerging countries such as China have been fuelling land use pressure in tropic forests and is thought of as a primary driver of deforestation in sensitive ecosystems such as the Amazon (zu Ermgassen et al., 2020). At the same time, illegal appropriation of public land for speculative reasons has been highlighted as another major driver of deforestation and has surged in recent years (e.g. Carrero et al., 2022), with weak land governance, as is often the case in emerging economies in the tropics, paving the way for it (Reydon et al., 2020). Land grabbing is often achieved by first illegally deforesting areas and then putting them to (apparent) agricultural use in order to claim ownership rights. In the context of the Brazilian Amazon cattle acts as the predominant vehicle for appropriation (Fearnside, 2017) and thus serves two purposes: (1) allowing for the illegal appropriation of lands, while (2) also increasing the value of the appropriated land with some form of agricultural use. As such, it remains unclear whether and to what extent the agricultural expansion in Brazil, and here especially the conversion to cattle pasture, is due to purely demand-driven considerations or serves as a vehicle for land appropriation.[1]

Against this backdrop, it seems to pertinent to have a good understanding of the effects that the various channels behind the agricultural expansion have. Yet, disentangling them remains a conundrum yet to be solved in the literature. In this paper, we propose

[1]This issue is also at the forefront in the academic debate. For example, De Oliveira Silva et al. (2021) state that in recent years "[...] grazing animals are used to facilitate conversion and signal ownership, rather than being the primary driver [...]" in the Amazon. This claim is contested by França et al. (2021), analyzing the extensive and intensive margins of the livestock industry in the Brazilian Amazon, and concluding that livestock intensification for the satisfaction of beef demand so far has not prevented pasture area extension in the Amazon.

an empirical specification to identify the *causal* effect of the *demand-driven* agricultural expansion on deforestation in the Brazilian Amazon. We use a shift-share design where we interact information about pre-existing production patterns, the share component of our Bartik instrument, with exogenous changes in the demand for beef products, the shift. For the construction of the share we rely on geo-referenced information of the location of export-eligible slaughterhouses in Brazil in conjunction with initial pasture area or cattle head shares. The shift part leverages changes in dietary habits in the largest importing market for beef products from Brazil, China. Alternatively, we use municipality-specific export statistics to incorporate information for all export destinations. The proposed approach isolates plausibly exogenous shifts in the demand for beef products from other factors behind the expansion of pasture and the livestock sector. This, in turn, allows us to identify the causal effects of the agricultural expansion on deforestation in Brazil.

Our results show that demand-driven agricultural expansion is a major driver of forest loss in the Brazilian Amazon and other endangered biomes in the period from 2003–2022. Increases in the area of pasture and the headstock of cattle to satisfy the growing demand for beef products displace forest and other vegetation at an alarming rate. In the Amazon, one additional hectare of pasture due to the growing demand of beef products reduces forest and forest-like vegetation cover by 0.75 and 0.81 hectare, respectively, whereas an additional unit of cattle reduces them by 0.51 and 0.62 hectare. We further show that some of these displacement effects extend also to other endangered biomes within Brazil such as the Cerrado, albeit in smaller magnitude. However, the displacement effects caused by the demand-driven agricultural expansion are weaker in more recent years. This weakening is confirmed by an analysis using an alternative instrument utilizing detailed municipality-level export statistics linking beef exports to destinations world-wide. We conjecture that other motives behind the agricultural expansion, such as land appropriation, have become more important in recent years. Moreover, additional results inform the debate surrounding the reconciliation of increasing agricultural production without increasing land pressure via the intensification of livestock.

We proceed as follows. The next section gives an overview deforestation and its drivers in Brazil, the significance and expansion of the Brazilian agriculture sector, and the Brazilian environmental policy landscape, and how it has been undermined. Against this background, we formulate our empirical specification in the subsequent section, before presenting our results based on it. We conclude with a brief discussion and an outlook for future research.

2 Background

The Amazon is the world's largest rainforest with an area of 5.5 square kilometres, of which around 60% are located within the borders of Brazil. It plays a crucial role in upholding biodiversity, harboring almost 7,000 tree types (Cardoso et al., 2017), as well as in the maintenance of a stable regional and global climate (Leite-Filho et al., 2021). Historically, the Amazon has acted as a carbon sink, with its forests sequestering greenhouse gases from the atmosphere. However, in the past decades roughly 17% of forests in the Amazon have been lost (MapBiomas, 2023) and continued deforestation leave it at risk to become a major carbon source (Gatti et al., 2021). More than 80% of cleared area was converted into agricultural land, with nine tenths thereof being converted to pasture (MapBiomas, 2023). In this section, we given an overview of the potential drivers behind deforestation more generally, the role of agriculture in the Brazilian Amazon more specifically as well as the Brazilian environmental protection landscape.

Drivers of deforestation

Generally, drivers of forest loss can be summarized as (a) commodity-driven deforestation, (b) shifting agriculture, (c) forestry, (d) wildfire, and (e) urbanization (Curtis et al., 2018). These factors are distributed unevenly over the globe, with commodity-driven deforestation being predominant in Latin America and the Brazilian Amazon in particular. In the region, shifting agriculture and wildfires have to be seen in the context of deforestation (Escobar, 2019; Mataveli et al., 2022), and forestry is rare (Curtis et al., 2018). Deforestation decisions themselves are impacted and driven by a variety of factors (Busch and Ferretti-Gallon, 2017) that one can summarize into ones that (a) affect the potential value of cleared land (e.g. agricultural suitability and mineral deposits), and (b) determine whether and to which extent this value can be realized and extracted (e.g. land tenure security, infrastructure).

In the context of the Brazilian Amazon, the value of land largely stems from resource extraction or potential for it. At present, the most prominent resources are two agricultural commodities — beef and soy (zu Ermgassen et al., 2020; Lima et al., 2019; Rajão et al., 2020). Both require large swaths of land and their expansion is facilitated by and concentrated along infrastructure such as roads or slaughterhouses in the case of beef. This is also visible in Figure 1, where, for example, in the state of Parà the expansion of new pasture area is mainly concentrated along the BR-163 and BR-230 highways. Both soy and and beef products have been specifically targeted with (voluntary) private-sector deforestation interventions, such as the Soy Moratorium and Cattle Agreements (Gibbs et al., 2015; Alix-Garcia and Gibbs, 2017), which seek to decouple the commodities from

Amazon deforestation. However, their impacts are limited by complex monitoring requirements and limited applicability (Gollnow et al., 2018; Soterroni et al., 2019), which is especially in the case of the beef industry due to leakage and indirect sourcing of cattle (Alix-Garcia and Gibbs, 2017). Another considerably source of (potential) land value are mineral deposits. Mineral extraction has been expanding into ecologically vulnerable regions (Luckeneder et al., 2021), and has been linked to deforestation in the Amazon (Sonter et al., 2017), though the direct land use footprint of industrial mining is comparatively limited (Giljum et al., 2022). Nonetheless, indirect effects, including potential increases in land value from prospects of future mineral extraction and associated infrastructure developments in the vicinity, remain a large threat to the Amazon.

Fluctuations in prices of agricultural goods are important factors influencing deforestation decisions (Assunção et al., 2015), and the high and rising demands for agricultural commodities are largely unshakable features of the times. Agricultural production in Brazil plays an important role in securing global food supplies, especially for satisfying growing demand for meat (and here mainly beef) products resulting from dietary changes in emerging markets such as China or the Middle East (zu Ermgassen et al., 2020; Cusack et al., 2021). Intensification of agricultural production might present an alternative to expansion into (relatively unproductive) forested areas in the Amazon (Garrett et al., 2018; Marin et al., 2022; Zalles et al., 2019). However, the effectiveness of agricultural intensification in reducing pressures at the extensive margin is contested (França et al., 2021) and there is evidence that deforestation adversely affects agricultural yields (Leite-Filho et al., 2021), threatening the sector in the progress.

Two further salient (historical) features of deforestation in Brazil are low costs of non-compliance with environmental legislation, and low value of forested public land (as opposed to appropriated land) — both for most individual actors (Carrero et al., 2022; Coelho-Junior et al., 2022; Souza-Rodrigues, 2019). These factors behind deforestation can be understood as impacting the perceived value of cleared and forested land, as well as the costs of deforestation. These values and costs are not only affected by the current situation (i.e. the current state of driving factors), but also by potential future situations and changes therein. This presents an additional alignment problem in addition to the alignment of individual and common interests (Souza-Rodrigues, 2019). These features give rise to lopsided deforestation-decisions, even if there is little agricultural value to gain from (cleared) land. Illegal deforestation on private properties is rampant (Coelho-Junior et al., 2022) and land grabbing unrelenting (and almost government-approved) (Carrero et al., 2022; Yanai et al., 2022), especially along highways and other newly accessible land (Ferrante et al., 2021; Pinheiro et al., 2016).

Agriculture and the beef industry in Brazil

The agricultural sector plays an important role in Brazil, both in the context of securing livelihoods of local landowners and regional development as well as a driver of forest loss and degradation. Agriculture and connected industries contribute roughly one quarter of overall economic output in Brazil in recent years (CEPEA, 2023) and provided employment for more than 18 million individuals in 2017 (Castro et al., 2020). The Brazilian beef industry in particular has been growing strongly in the past decades (zu Ermgassen et al., 2020) and contributed around 8% of total GDP in Brazil (CEPEA, 2023). While the contribution of the overall agribusiness sector to Brazil's economic output has decreased by roughly a sixth, the contribution of livestock farming alone has more than doubled to around 2.6% of GDP in 2023 (CEPEA, 2023). While large, consolidated farms are responsible for the bulk of production of agricultural products in general and beef products in particular, small farms (up to 100 hectare) constitute almost 90% of all farms, highlighting the importance of the sector also for individual landowners (Rada et al., 2019).

Seen as a way for the development of remote areas and increasing prosperity among rural farmers and landowners, the Brazilian government actively encouraged the agricultural expansion in hitherto unexploited natural landscapes (Brancalion et al., 2016; Garrett et al., 2021). In this context, beef cattle was the predominant vehicle to lay claim on new areas on the agricultural frontier, whereas croplands were often converted from areas previously used as pasture (Molossi et al., 2023). Historically, the beef industry, including breeding and pasture areas as well as downstream industries for the processing of cattle (e.g. slaughterhouses), was concentrated in the biomes of the Cerrado and Atlantic Forest in the South of Brazil (Vale et al., 2022). Since the 1990s, a shift of production expansion towards the North, into the Amazon biome, has been particularly pronounced. By now, the centre of the beef industry infringes on the Amazon biome. Despite increases in the productivity of existing pasture, i.e. intensification of livestock, up until recently this expansion mainly took place at the extensive margin, i.e. by replacing pristine forest with additional pasture (Molossi et al., 2023). The Brazilian Amazon has been disproportionately affected by these trends in recent years. Whereas cattle herds and pasture areas have stagnated or slightly decreased in other biomes in Brazil, they have continuously expanded in the Amazon (França et al., 2021). Furthermore, for areas where intensification of livestock has occurred, adverse effects on sensitive ecosystems such as the Amazon have been documented (Vale et al., 2019).

The unparalleled expansion of the beef industry in recent years led to Brazil becoming the world's second-largest producer, trailing only the United States, and the largest exporter globally for beef products (zu Ermgassen et al., 2020). Both the production and export of beef products grew steadily over the past decades with the exception of exports reducing during the 2014–2016 recession caused by a devaluation of the Brazilian Real. Within the portfolio of export markets, especially exports to emerging markets have skyrocketed and China with its dependencies has become the largest export market for Brazilian beef products, accounting for roughly two thirds of total exports nowadays (UN Comtrade, 2022). The Brazilian beef processing sector is the world's largest and dominated by three large meatpacking companies—JBS, Marfig, and Minerva—that account for roughly 50% of the country's market (Vale et al., 2022). These meatpackers are central for the coordination of overall beef production and have signed voluntary zero-deforestation commitments—the so-called Cattle Agreements—that aim to ban deforestation-implicated cattle from their supply chains. These agreements could play an important role in curbing Amazonian deforestation (Levy et al., 2023) but are prone to evasion through the indirect supply of cattle raised on illegally deforested land (Alix-Garcia and Gibbs, 2017).

Deforestation interventions and their undermining in Brazil

The expansion of pasture areas and cattle placed upon them play a dual role in the Brazilian Amazon, namely to satisfy the growing demand for beef products and as a vehicle for land appropriation (Fearnside, 2017). Especially the latter channel has been facilitated by changes in Brazil's legal framework for sustaining natural vegetation and curbing deforestation in the past decades. Originally established already in the 1930s, the Native Vegetation Protection Law, colloquially referred to as the Forest Code (FC), regulates forest clearings on private land and is the cornerstone of Brazilian environmental legislation. It regulates, inter alia, the proportions of natural vegetation that have to be preserved on private properties (e.g. 80% in the Amazon biome) and has been strengthened and clarified in several rounds revisions (Brancalion et al., 2016).

Together with the introduction of a system that formalized different categories of protected area, the advent of advanced satellite-based monitoring systems, and sufficient political support under the government of Luiz Inácio Lula da Silva (Lula) rampant deforestation rates were reduced by over 80% in the 2000s (Garrett et al., 2021). Important elements that were effectively reducing deforestation rates were the launch of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) (Assunção et al., 2015), private-sector initiatives such as the Soy Moratorium (Heilmayr et al., 2020), as well as other integrated deforestation actions such as the establishment of priority municipalities (Assunção and Rocha, 2019) and restraints for rural credit extension tied to environmental performance (Assunção et al., 2020). The efficacy of law enforcement as such has been shown for this earlier periods (Hargrave and Kis-Katos, 2013) but has been diminishing in recent years (Kuschnig et al., 2023).

Subsequent changes in the FC and other parts of the legislative framework brought about both advances and setbacks for environmental conversation efforts (Garrett et al., 2021). Importantly, the FC and its regulations are only applicable to private land. To effectively allow monitoring deforestation on private properties, the *Cadastro Ambiental Rural* (CAR), a registration system for rural properties, was established in 2012. It is thought of as the primary barrier to land grabbing (Chiavari et al., 2020), but can itself be misused for land appropriation without pending completion and validation of the system due to its self-referenced nature (Carrero et al., 2022). 17% of the Brazilian land are lacking a clear form of tenure and 54.6 million hectares of public land are undesignated (6% of the total area), with a majority of it in the Amazon (Sparovek et al., 2019). In these areas, land grabbing is prevalent, and forested lands are cleared, occupied illegally, and subsequently appropriated (Carrero et al., 2022). During the presidencies of Dilma Rousseff and Michel Temer, both heavily influenced by the agribusiness sector (Garrett et al., 2021), several amendments were adopted that influenced perceptions of the consequences for illegal deforestation and land grabbing. In 2012, amnesties for illegal deforestation on private properties prior to 2008 saw landowners absolved from restoration obligations, artificially reducing Brazil's "environmental debt" by 58% (Soares-Filho et al., 2014). Further amnesties for land appropriations in the Amazon biome between 2005–2011 together with increases of the maximum amount of claimable land to 2,500 hectares per farm in 2017 facilitated and accelerated land grabbing of previously illegally deforested areas (Rochedo et al., 2018; Brito et al., 2019).

The two most recent governments, under president Jair Bolsonaro in the years 2019–2022 and under Lula since 2023, are largely diametrical in their approach to environmental conservation. The former was characterised by unparalleled attempts to dismantle environmental protection agencies and legislation, including effectively paralysing institutions responsible for forest protection through increased bureaucratic burdens, reduced budgets and purposefully leaving key positions vacant (Ferrante and Fearnside, 2019; Kuschnig et al., 2023), and aggressive rhetoric that has been linked to higher deforestation (Oliveira et al., 2023). Lula has put environmental concerns and promises at the core of its political agenda again and, encouragingly, deforestation rates in the months following his inauguration have reduced by roughly 20% (mon, 2023). Nonetheless, both past and recent statements from as well as certain staffing decisions under Lula, which included the minister of agriculture Carlos Fávaro, and political resistance from the agricultural bloc of the Brazilian National Congress require (international) scrutiny with regards to the achievement of the ambitious goals set by the government (Vilani et al., 2023).

3 Disentangling the agricultural expansion

In this section we describe the empirical approach that we use to isolate the causal effect of the demand-driven expansion of agriculture, detailing the empirical approach and our identification assumptions, as well as describing the used data.

Empirical Specification

We are interested in computing the effect of the agricultural expansion on deforestation and start from a simple panel regression setup at the municipality-year level:

$$y_{i,t} = \boldsymbol{X}_{i,t-s}\boldsymbol{\gamma} + \beta c_{i,t} + u_{i,t}, \quad u_{i,t} \sim \mathcal{N}(0, \sigma_y^2) \tag{1}$$

where $y_{i,t}$ is deforestation (forest loss) in municipality i ($i = 1, \dots, N$) in year t ($t = 1, \dots, T$), $\boldsymbol{X}_{i,t}$ is a vector of (suitably lagged) covariates influencing deforestation within a municipality (including municipality- and year-fixed effects as well as municipality-specific time trends), $c_{i,t}$ is a measure for cattle/pasture expansion (e.g. change in pasture area or cattle headcount) or intensification (e.g. cattle density), and $u_{i,t}$ is a Gaussian error with zero mean and (homoskedastic) variance σ_y^2.

In the naive panel regression of Equation 1, the coefficient of interest, β, is not, in general, identified due to various endogeneity issues, capturing various drivers of the expansion (e.g. increasing demand for beef products and land appropriation/speculation). To allow for a causal interpretation of it, we rely on a *shift-share* (or Bartik) instrumental variable approach (Jaeger et al., 2018; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), where we instrument the endogenous variable $c_{i,t}$ with the Bartik instrument $B_{i,t}$, controlling for covariates $\boldsymbol{X}_{i,t}$, in the first stage (Equation 3):

$$y_{i,t} = \boldsymbol{X}_{i,t-s}\boldsymbol{\gamma} + \beta \hat{c}_{i,t} + u_{i,t}, \quad u_{i,t} \sim \mathcal{N}(0, \sigma_y^2) \tag{2}$$

$$c_{i,t} = \boldsymbol{X}_{i,t-s}\boldsymbol{\alpha} + \omega B_{i,t} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_c^2) \tag{3}$$

$$B_{i,t} = z_{i,t=0}\, g_{t-1}, \tag{4}$$

where our instrument, $B_{i,t}$ is constructed as product of a measure for exposure to deforestation pressure via cattle expansion in an initial period (the *shares*), $z_{i,t=0}$, and (exogenous) changes in the demand for beef products (the *shift*), g_t. Given an appropriately constructed instrument, this approach allows us to isolate the effects due to changes in the demand for agricultural products, focusing on cattle and related beef products.

In our setup, the *shares* should be a strong predictor for the expansion of pasture area (and the cattle placed on them) and can be constructed in various ways. One can deduce from Figure 1 that the expansion of pasture is clustering around pre-existing pasture areas. Furthermore, Figure B1 in the appendix shows that the location of slaughterhouses is also closely related to the existence of pasture areas and their expansion, as are openings of new ones related to the expansion of pasture areas. We combine these insights for the construction of our shares. Specifically, we utilize geocoded data on federally inspected slaughterhouses (SIF, eligible for exports) from Vale et al. (2022) and combine it with information about pasture areas or cattle head in municipality i or its vicinity as follows:

$$z_{i,t=0} = \exp\{-1/d_{i,t=0}\} \times \frac{1}{C_{t=0}} \sum_k c_{k,t=0}\,, \tag{5}$$

where $d_{i,t=0}$ denotes the distance of municipality i to the nearest SIF slaughterhouse,[2] $C_{t=0}$ denotes aggregate pasture area or cattle head in the larger region under investigation (e.g., the Legal Amazon), and $\sum_k c_{k,t=0}$ is the sum of pasture area or cattle head in municipality i and its neighbours as determined by contiguity.[3] This interaction captures the notion that pre-existing production patterns, both in the form pasture area and processing facilities for beef products, are important predictors for the future expansion demand-driven agriculture. As base period, we use slaughterhouse locations for those active in the period from 2000 to 2002 and the average municipality i's share on total pasture area or cattle head in the same period. For specifications investigating the effect of changes in cattle density, we use the mean cattle density for municipality i in the same time period instead.

For the *shift* component of our instrument, g_t, we leverage information about changes in beef consumption in the main export markets for Brazilian beef products. Here, we exploit the fact that changes towards a more meat-oriented (and in particular beef-oriented) diet in emerging markets in this period were a strong exogenous shift due to increases in average incomes in these markets. More specifically, in the main part of the our analysis we use data on Chinese beef consumption for the construction of our shock.[4] Figure B2 in the appendix shows that Chinese beef consumption per capita has increased by over 50% in recent decades, while still exhibiting substantial yearly fluctuations that we exploit as source for our exogenous shocks. As described earlier and also shown in Figure B2, beef exports to China have skyrocketed and it has become the largest exporting market for Brazilian beef products over the last decades, by now accounting for almost two thirds of

[2] We measure distance in hundreds of kilometers and compute it from the nearest edge of a municipality's polygon to the point location of the slaughterhouse. In case the slaughterhouse is located within a municipality we compute the distance between a municipality's centroid and the slaughterhouse.

[3] One could also use pasture area or cattle head directly or the respective measure of municipality i only. However, with the chosen specification we (i) retain the interpretation as shares by being bounded between zero and one and (ii) take into account agglomeration effects that potentially span across boundaries of individual municipalities. Results based on pasture area or cattle head and incorporating only municipality i's information for the interaction with our distance measure yielded similar results.

[4] Note that, for the most part of our study, we define China as consisting of China mainland, Hong Kong, and Macao.

all such exports (in value).[5] The importance of changes in Chinese beef consumption for the (external) demand for Brazilian beef products together with its plausibly exogenous nature with respect to local (i.e. municipality-level) conditions make it a suitable shift component for our Bartik instrument. To account for the fact that observed variations in consumption and related exports affect demand for the inputs of production (in particular land) with a delay, we use lagged changes in Chinese beef consumption in the construction of $B_{i,t}$. Our primary research design thus leverages pure time-series shocks and is conceptually close to the studies by Nunn and Qian (2014) that investigate the effect of US food aid on violent conflict or by Droller (2018) studying the impact of population composition on lung run economic development in Argentina.

However, as a validation for our main results, we also construct a shift-share instrument that resembles such an approach by utilizing information about the destination of beef exports on a municipality level. This approach is related to studies that construct their instruments as the weighted sum of many shocks.[6] Specifically, in this setting, our Bartik instrument is constructed as:

$$B_{i,t} = \sum_{m} z_{i,m,t=0}\, g_{m,t}, \quad z_{i,m,t=0} = z_{i,t=0} \times \frac{\text{exports}_{i,m,t=0}}{\text{exports}_{i,t=0}}, \tag{6}$$

where $z_{i,t=0}$ is defined as above. The second term for the construction of the export market-specific share variable $z_{i,m,t=0}$, where $m = 1, \ldots, M$ denotes export markets, is based on municipality-specific export shares for beef products retrieved from zu Ermgassen et al. (2020). The Bartik instrument $B_{i,t}$ is then the weighted sum of shocks to beef consumption growth in market m, retrieved from FAO (2023). Thus, instead of shifting the instrument by changes in Chinese beef consumption only, we shift it with the corresponding measure of all export partners that municipality i had at initial time period $t = 0$. The choice of the initial time period is dictated by the availability of data from zu Ermgassen et al. (2020), who provide information on this granular level from 2015–2017 only.[7]

[5] Exports of beef products to other countries similarly have been trending upwards, especially for markets located in Asia (e.g. Vietnam) or the Middle East and North Africa (e.g. Egypt).

[6] Prominent examples include Autor et al. (2013) on the effects of Chinese import competition on US labor markets, Card (2009) on the effects of immigration on local labor markets in the US, or Hummels et al. (2014) on offshoring activities of Danish firms. These and other studies, and their implications, are thoroughly analysed in the recent literature on shift-share IV regressions designs (see e.g. Jaeger et al., 2018; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

[7] We report results where we fixed the initial period at 2015 to maximize the time dimension of the resulting panel. A handful of municipalities that recorded no exports in 2015 did so in subsequent year. As sensitivity check, we also used specifications where we used export shares from the first year they reported non-zero export flows as well as from years with the highest exports or number of export partners as sensitivity checks. Results were qualitatively and quantitatively similar across all these specifications.

Identification

For our identification strategy to be valid, we have to *a priori* argue that either one of the two components of our instruments, the share or the shift, has to be exogenous. We follow Borusyak et al. (2022) and view the shift component g_t, in our case changes in international (in particular, Chinese) beef consumption, as exogenous. While this conjecture cannot be assessed empirically, we argue that it is unlikely that such consumption shocks affect deforestation in municipality i at time t in other ways than through the expansion of production inputs for beef products (in particular land) to satisfy demand them. Further, we argue that dietary changes in China and other emerging markets have been driven primarily by changes in incomes within them and are thus plausibly exogenous with respect to local economic or environmental conditions in a given Brazilian municipality.[8] To further strengthen the validity of our instrument, we include a range of other time-varying controls in $\boldsymbol{X}_{i,t-s}$ as described in the next subsection.

Data

We obtain all our data from openly available sources. Where necessary, we process and aggregate them to the municipal level for all municipalities that are majorly in the Amazon, Cerrado, or Pantanal biomes, leaving us with a cross-sectional dimension of $N = 1,574$. After all transformations and suitably lagging certain variables, our dataset covers the time period 2002–2023. See Table A1 in the appendix for a detailed description of variables, their transformations and sources.

Main Variables: Data for land use and land use transitions are taken from the Brazilian Annual Land Use and Land Cover Mapping Project (MapBiomas, 2023). It tracks land use at a spatial resolution of 30 by 30 meters for the period 1985–2022 and provides summary statistics for land use and land use change at the municipal level. We construct measures for forest and forest-like vegetation (i.e. including savanna) loss in two ways: once using the difference in the area of the respective type of land cover and once using the sum off all transitions from the respective vegetation type towards non-forest formation. While the former measures net vegetation loss within a given municipality, the latter measures gross vegetation loss. Similarly, we define the net change in pasture area as difference in total pasture area and gross pasture gain as all transitions from other uses

[8] Agricultural prices, in particular for beef products, on international markets and in Brazil have, on average, increased strongly in recent decades, despite temporary price drops. Price increases on a global scale reflect predominantly shifts on the demand side and are essentially fixed for a given municipality (with the exception of additional transport costs potentially borne by the producer). To account for these effects, we control for agricultural commodity price fluctuations on the municipality level by including price indexes constructed akin to Assunção et al. (2015).

towards pasture. As additional measures for the expansion of the beef industry, we use the headstock of cattle within a given municipality, retrieved from the Instituto Brasileiro de Geografia e Estatística (IBGE) and compute cattle density, defined as the number of cattle per hectare of pasture, as a measure for the intensive margin of beef production (IBGE, 2022).

Controls: Following Equation 1, we control for a set of time-varying covariates at the municipal level. We include socioeconomic conditions and developments measured by changes in total population and gross domestic product (GDP) per capita, both obtained from the IBGE (IBGE, 2022). To account for changes in prices of agricultural goods, we follow Assunção et al. (2015) and construct price indices based on the interaction of commodity prices as reported by the agricultural ministry of the state of Paraná and commodity-specific land cultivation information taken from MapBiomas (2023). As policy-related variables we include the total number of environmental fines for flora-related offenses as reported from IBAMA (IBAMA, 2022) and the share of indigenous land on total municipal area from the World Database on Protected Areas (UNEP-WCMC and IUCN, 2022). Finally, we also include meteorological conditions in the form of an indicator for dry spells based in the Normalized Difference Vegetation Index (NDVI) from Beguería et al. (2010).

Shift-share Instrument: For the share part of our instrument we use geo-referenced information on the location of federally inspected slaughterhouses, provided by Vale et al. (2022), and interact it with pre-existing production patterns for both pasture areas, taken from MapBiomas (2023), and cattle head or density, taken from IBGE (2022). For parts of our analysis, we rely on municipality-level export statistics of beef products from zu Ermgassen et al. (2020). The shift part of our instrument, changes in beef consumption in China or all export destination markets, are taken from FAO (2023) and is measured in tons of total human consumption of beef products.

4 Results

In this section, we briefly describe the main results of our empirical analyses. Sections C–E in the appendix provide our full results, including heterogeneity and sensitivity analyses.

4.1 First Stage Regression

Table C1 reports the results of the first stage of the IV regressions following Equation 3, regressing various measures for the agricultural expansion on the respective instrument $B_{i,t}$. It can be discerned that our instrument is a strong predictor for the future agricultural expansion in our preferred specification with municipality-specific time trends.

F-statistics are well above the conventional rule-of-thumb value of 10 (Staiger and Stock, 1997). An increase in the constructed instrument leads to a strong increase in the various expansion measures under consideration.

4.2 Baseline Results

Table 1 reports that pasture expansion due to agricultural demand pressures is a significant driver of forest and related vegetation loss in Brazil, particularly so in the Amazon. The identified coefficients imply that a one-hectare increase of pasture caused by an agricultural expansion reduces cover of forest-like vegetation (including e.g. savanna) by 0.98 hectare in the biomes of the Amazon, Cerrado and Pantanal, by 0.91 hectare in the Legal Amazon and 0.93 hectare in the Amazon biome. When considering forest loss only, these effect sizes drop, as can be expected, the most for the broadest sample including the three biomes mentioned above. In the Cerrado biome, pasture mainly replaces savanna-like vegetation, thereby reducing the impact of demand-induced pasture expansion on forest loss. For the Legal Amazon (that includes municipalities also lying the Cerrado biome) and the Amazon biome, the estimated coefficients of -0.75 and -0.79 imply strong reductions in forest cover caused by the demand-driven expansion of pasture ares. The effects of an expansion of the cattle stock are similarly striking. Whereas their OLS counterparts only show a weak, negative correlation with forest and forest-like vegetation loss, the IV estimates unveil strong, negative effects. An additional unit of cattle on average decreases forest cover by -0.51 to -0.62 hectare in the various specifications, with the strongest effects occurring for municipalities in the Amazon biome. These estimates seem reasonable given an average cattle stocking rate of 0.97 animal units per hectare in Brazil (Arantes et al., 2018).

4.3 Heterogeneity Analysis

Table 2 contrasts effects in the Legal Amazon for the whole period of investigation (2003–2022) with the post-2015 period, where the instrument is constructed using information on municipality-specific export shares by destination. For pasture, effects of the demand-driven expansion are estimated to be lower in more recent years. Reassuringly, the estimates across the specifications of our instrument, ranging from -0.61 to -0.63. On the contrary, the alternative specification based on export shares in the construction of the instrument reveals that despite increases in cattle headstock still has a negative effect on forest cover in the Legal Amazon, this effect has been more muted in recent years. This drop in effect size could be interpreted in various ways. For once, land pressure from the agricultural expansion could have reduced in the later period, with

Table 1: IV regressions: Agricultural expansion and deforestation

	Biomes AMA, CER, PAN		Legal Amazon		Amazon biome	
	OLS	IV	OLS	IV	OLS	IV
			Δ forest-like vegetation cover			
ΔPasture	-0.688***	-0.981***	-0.728***	-0.905***	-0.781***	-0.932***
	(0.043)	(0.065)	(0.042)	(0.080)	(0.040)	(0.084)
ΔCattle	-0.018***	-0.888***	-0.020***	-0.623***	-0.021***	-0.737***
	(0.005)	(0.267)	(0.007)	(0.147)	(0.008)	(0.173)
			Δ forest cover			
ΔPasture	-0.604***	-0.580***	-0.676***	-0.752***	-0.746***	-0.788***
	(0.055)	(0.118)	(0.051)	(0.081)	(0.047)	(0.074)
ΔCattle	-0.015***	-0.533***	-0.020***	-0.508***	-0.020**	-0.620***
	(0.005)	(0.182)	(0.007)	(0.147)	(0.008)	(0.158)
Fit statistics						
Observations	31,480	31,480	16,160	16,160	10,060	10,060
F-test, ΔPasture		758.96		577.53		438.62
F-test, ΔCattle		32.519		62.516		33.854

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1, using OLS in odd columns and the IV specification in even columns. The first two columns hold results for all municipalities in the Cerrado, the Amazon and the Pantanal biomes, the third and fourth columns for all municipalities in the nine states that constitute the Legal Amazon, and the last two columns for municipalities that are either fully or partly in the Amazon biome. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. Models include municipality and time fixed effects as well as a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

intensification of livestock becoming more prevalent (Molossi et al., 2023). On the other hand, this result might also provide suggestive evidence that in recent years other factors behind the agricultural expansion, such as land appropriation motives, have become more important. This conjecture is to a certain extent supported by the stark increase in anti-environmental rhetoric in the political discourse during this period, especially during the presidency Jair Bolsonaro which has been shown to increase forest fires and related forest loss (Oliveira et al., 2023).

4.4 Intensification

Finally, Table 3 provides some suggestive evidence that livestock intensification could decrease land pressure from agricultural production. As reported also above, both an increase of pasture area and cattle headcount decrease forest cover significantly in municipalities in the Legal Amazon. However, an increase in the cattle density, used as a proxy for livestock intensification, reduces forest loss, when keeping the cattle head stock constant. This result gives an indication that by more intensive use of available pasture could indeed decrease pressure on forested land. A word of caution should be made with respect to our measure for intensification, namely cattle density that we define as number

Table 2: IV regressions: Alternative instrument, post-2015 period

Legal Amazon, Δforest cover

	Whole period		Post-2015		
	OLS	IV-int	OLS	IV-int	IV-exp
ΔPasture	-0.676***	-0.752***	-0.538***	-0.605***	-0.632***
	(0.051)	(0.081)	(0.070)	(0.115)	(0.125)
ΔCattle	-0.020***	-0.508***	-0.006	7.62	-0.072**
	(0.007)	(0.147)	(0.006)	(218.5)	(0.030)
Fit statistics					
Observations	16,160	16,160	5,656	5,656	5,656
F-test, ΔPasture		577.53		161.21	81.956
F-test, ΔCattle		62.516		0.01280	19.726

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the Legal Amazon. The first two columns hold results for the whole period (2003–2022), the latter three columns for the post-2015 period. The fourth column presents IV results using the instrument with shares as specified in Equation 5, the fifth columns with shares and shift as defined in Equation 6. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. Models include municipality and time fixed effects as well as a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

of cattle per hectare of pasture. Using such a simple measure for agricultural intensification is likely to miss out some important aspects such as the concentration of production units in vertically integrated units. Furthermore, the result that intensified livestock production, defined as a higher cattle density, might reduce land pressure and deforestation should be reflected with the other adverse environmental effects that it could have. This includes potential groundwater pollution due to more concentrated animal waste and resulting forest degradation, as has been documented for the expansion of intensified beef farming in the Brazilian Amazon (Vale et al., 2019).

4.5 Robustness Checks

Table E1 in the appendix documents the results for various sensitivity checks. In particular, it reports results for specifications where we (i) restrict the sample to municipalities that had at least ten percent forest cover in 2002 and experienced forest loss in the period until 2022, (ii) use the contemporary change in Chinese beef consumption as shift variable instead of its lag , and (iii) use lagged values for the measures of the agricultural expansion. Results for these robustness checks are qualitatively and quantitatively are largely similar to our main results. However, there are two exceptions. First, the effect of cattle density becomes insignificant, if we restrict our sample. This could be an indication that the effects of livestock intensification have been successful only in those municipalities that did not exhibit forest loss in the past decades, a rather unsurprising result. Second, the

Table 3: IV regressions: Intensification results

	Legal Amazon, Δforest cover					
	OLS	IV	OLS	IV	OLS	IV
ΔPasture	-0.676***	-0.752***				
	(0.051)	(0.081)				
ΔCattle			-0.020***	-0.508***		
			(0.007)	(0.147)		
ΔCattle Density					0.002	0.27***
					(0.002)	(0.055)
Fit statistics						
Observations	16,160	16,160	16,160	16,160	16,160	16,160
F-test, (1st stage)		577.53		62.516		432.84

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1, using OLS in odd columns and the IV specification in even columns for the Legal Amazon. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. Models include municipality and time fixed effects as well as a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

effect of an increase in the cattle headstock flips sign if we use the unlagged instrument in our specification, most often becoming insignificant. We can rationalize this finding by considering that demand-induced shocks are unlikely to increase cattle herds within the same year given that cattle needs to be raised and responds therefore with a lag. This could in turn mute the mediated effect on deforestation.

5 Conclusion & Outlook

The expansion of agriculture is one of the main drivers behind the continued deforestation in the Brazilian Amazon, threatening biodiversity, the regional and global climate, as well as a number of other ecosystem services provided by the rainforest. In this paper, we analyzed the different motivations and mechanisms behind this expansion, and estimated causal effects of the rise in agricultural production on deforestation rates. We showed that this rise, stemming from a growing global demand for beef, is one of the major drivers of deforestation. Our results revealed that both the expansion of pasture area and an increase in the head stock of cattle cause stark reductions in forest or forest-like vegetation cover, particularly so in the Amazon biome. However, our results suggested that these effects have become weaker in recent years, in which deforestation has surged. We interpreted this as evidence for the increasing importance of other related motives, such as land grabbing. Lastly, we provided evidence that livestock intensification could play an important role in decreasing land pressure from agricultural expansion.

The potential avenues for future research are manifold. In the context of this study, more detailed analyses of heterogeneity, e.g., along the dimensions of time and biome could yield deeper insights into the dynamics of the agricultural expansion. While we provided suggestive evidence for weak land governance and land appropriation, with land values ultimately governed by agricultural productivity, becoming increasingly important drivers of deforestation, deeper investigations are warranted. Another important alley for future research concern the incorporation of these dynamics into analyses of existing and proposed interventions; the *Cadastro Ambiental Rural*, e.g., set out to improve land governance, but has arguably been turned into a vehicle for land appropriation.

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A Data description

Table A1: Variable description

Variable	Description	Main source(s)
Forest cover	Forest Formation (class ID 3), in hectare	MapBiomas (2023)
Savanna cover	Savanna Formation (class ID 4), in hectare	MapBiomas (2023)
Forest-like vegetation cover	Forest-like vegetation formation; including Forest Formation (3), Savanna Formation (4), Flooded Forest (6), and Forest Plantation (9), in hectare	MapBiomas (2023)
Gross forest loss all	Sum of transitions from forest formation towards non-forest formation, in hectare	MapBiomas (2023)
Gross savanna loss all	Sum of transitions from savanna formation towards non-forest formation, in hectare	MapBiomas (2023)
Gross forest-like vegetation loss all	Sum of transitions from forest, savanna, or flooded forest formation and forest plantations towards non-forest formation, in hectare	MapBiomas (2023)
Pasture	Area used as pasture (class ID 15), in hectare	MapBiomas (2023)
Pasture gain gross	Sum of transitions towards pasture, in hectare	MapBiomas (2023)
Gross domestic product	Real gross domestic product index, in constant BRL	IBGE (2022)
Population	Population headcount	IBGE (2022)
Cattle	Cattle headcount	IBGE (2022)
Cattle density	Number of cattle per hectare of pasture area	IBGE (2022)
Environmental fines	Number of fines for flora-related offenses	IBAMA (2022)
Protected areas	Share of municipality area designated as protected areas, including indigenous areas	UNEP-WCMC and IUCN (2022)
Agricultural prices	Indices constructed as weighted sum of commodity prices as reported by the agricultural ministry of Paraná following Assunção et al. (2015), weights derived from land use statistics	Ministry of Agriculture – Paraná; MapBiomas (2023)
SPEI dry	Indicator for dry spells based on the Normalized Difference Vegetation Index (NDVI)	Beguería et al. (2010)
Slaughterhouse distance	Distance to federally inspected slaughterhouses (eligible for export of beef products)	Vale et al. (2022)
Beef consumption	Human consumption of beef products, in thousand tons	FAO (2023)

Notes: Table shows variables used in regressions on a municipality-level and variables used for construction of the shift-share instrument, a short description and their sources.

B Additional figures

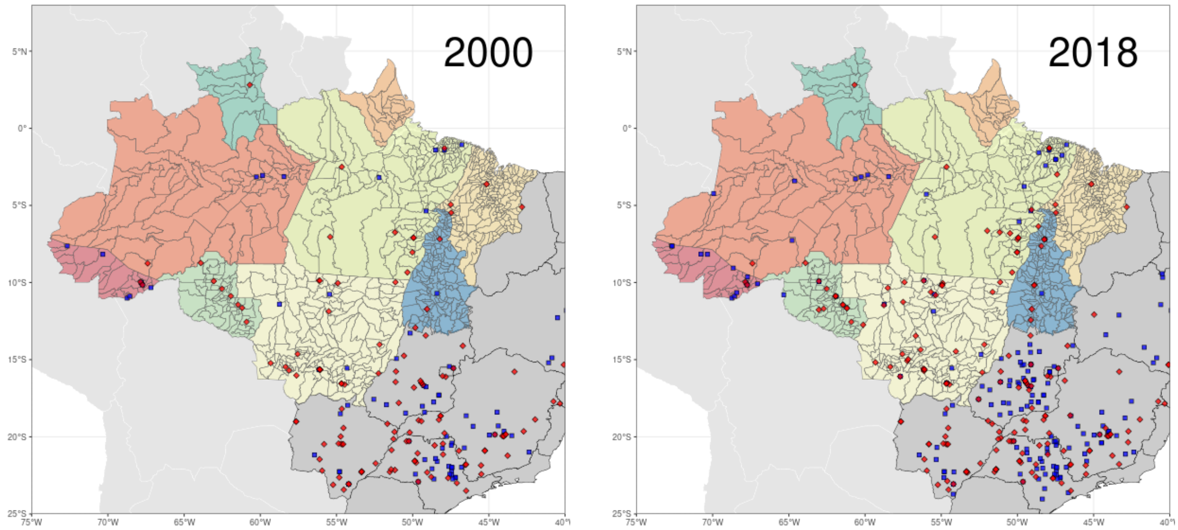

Figure B1: Slaughterhouse locations in 2000 and 2018. Red trapezes denote SIF slaughterhouses, blue squares non-SIF slaughterhouses. Source: Vale et al. (2022)

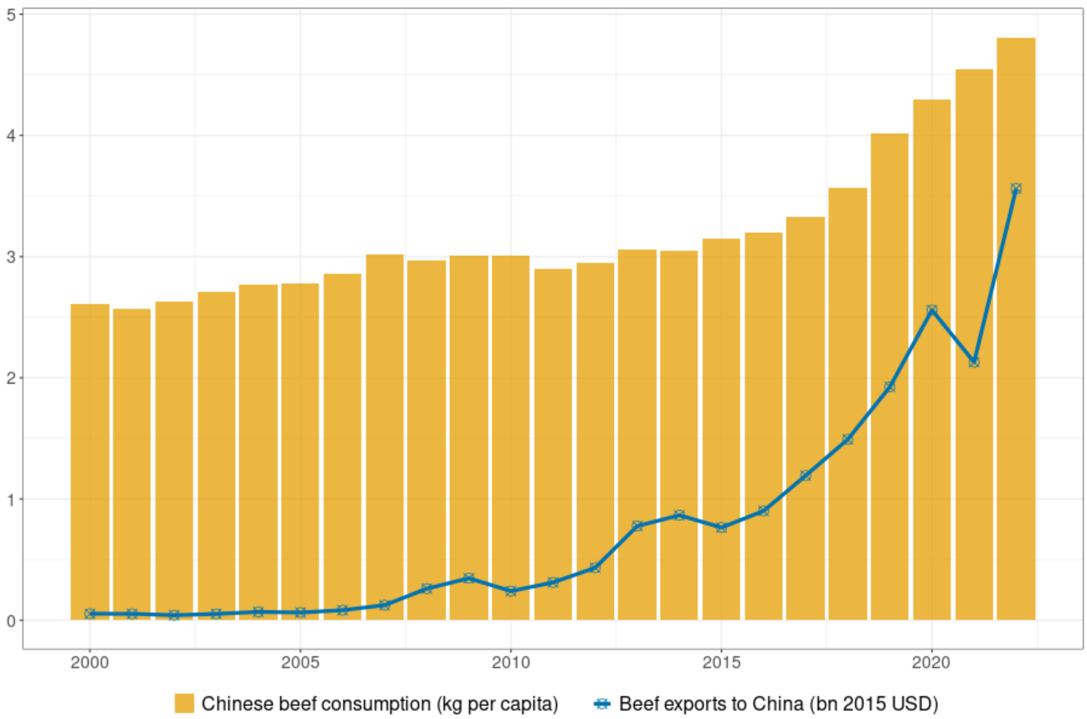

Figure B2: Chinese per capita beef consumption and Brazilian exports of beef products to China. Sources: FAO (2023) & UN Comtrade (2022)

C Main Regression results

C1 First stage results

Table C1: First stage results for IV specification

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Biomes Amazon, Cerrado and Pantanal					
	Pasture			Pasture Gain		
Pasture IV$_{t-1}$	1,052.9*	1,125.7	2,947.0***	567.9	748.3	1,685.8**
	(615.7)	(799.2)	(727.6)	(549.9)	(712.6)	(673.5)
F-test (1st stage)	113.49	97.010	758.96	54.109	71.643	432.97
	Cattle			Cattle Density		
Cattle IV$_{t-1}$	427.9	1,574.1**	2,705.4**	-0.0003***	-0.0003***	0.0003***
	(745.5)	(797.0)	(1,173.1)	(9.35×10^{-5})	(9.29×10^{-5})	(3.76×10^{-5})
F-test (1st stage)	1.2581	11.902	32.519	566.92	573.72	843.47
Observations	31,480	31,480	31,480	31,480	31,480	31,480
	Legal Amazon					
	Pasture			Pasture Gain		
Pasture IV$_{t-1}$	1,440.9**	1,358.8	2,756.0***	1,005.9	1,162.0	2,001.4***
	(716.1)	(826.1)	(835.8)	(645.3)	(727.3)	(763.8)
F-test (1st stage)	181.84	136.77	577.53	132.54	152.33	486.96
	Cattle			Cattle Density		
Cattle IV$_{t-1}$	1,792.3***	1,455.9**	3,528.7***	-0.0003***	-0.0003***	0.0003***
	(540.4)	(591.3)	(1,020.1)	(9.34×10^{-5})	(9.29×10^{-5})	(3.75×10^{-5})
F-test (1st stage)	24.592	13.780	62.516	288.82	293.68	432.84
Observations	16,160	16,160	16,160	16,160	16,160	16,160
Fixed-effects						
muni_id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	No	Yes	Yes	No	Yes
State-year FEs	No	Yes	No	No	Yes	No
Municipality-specific trends	No	No	Yes	No	No	Yes

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows first-stage results for IV estimation of Equation 3 for the whole period (2003–2022), for all municipalities in the Cerrado, the Amazon and the Pantanal biomes in the upper panel and for the Legal Amazon in the lower panel. All models use the instrument based on the shares as specified in Equation 5. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality fixed effects, models in columns (1) and (4) include year fixed effects, models in columns (2) and (5) include state-year fixed effects, models in columns (3) and (6) include a municipality-specific linear time trend. Standard errors are clustered at the municipality level.

C2 Second stage results

Table C2: Regression results for biomes Amazon, Cerrado, Pantanal

Model:	OLS (1)	IV-int (2)	IV-share (3)	OLS (4)	IV-int (5)	IV-share (6)	OLS (7)	IV-int (8)	IV-share (9)
Dependent Variable:	Difference in forest-like vegetation cover								
Pasture	-0.727***	-1.27***	-1.18***	-0.718***	-1.40***	-1.32***	-0.688***	-0.981***	-0.935***
	(0.036)	(0.225)	(0.183)	(0.039)	(0.337)	(0.259)	(0.043)	(0.065)	(0.059)
Cattle	-0.025***	-2.86	-1.08	-0.021***	-1.03*	-0.663**	-0.018***	-0.888***	-0.661***
	(0.006)	(4.48)	(0.662)	(0.006)	(0.600)	(0.303)	(0.005)	(0.267)	(0.181)
Cattle Density	1.64	-22.5**	-22.1**	5.79**	-66.4**	-59.4*	1.24	20.3***	25.8***
	(1.49)	(9.81)	(10.7)	(2.57)	(32.6)	(31.6)	(1.69)	(3.36)	(8.86)
Dependent Variable:	Difference in forest cover								
Pasture	-0.646***	-0.894***	-0.853***	-0.639***	-0.959***	-0.905***	-0.604***	-0.580***	-0.574***
	(0.048)	(0.180)	(0.155)	(0.050)	(0.197)	(0.171)	(0.055)	(0.118)	(0.089)
Cattle	-0.022***	-2.02	-0.753	-0.018***	-0.727	-0.458*	-0.015***	-0.533***	-0.404***
	(0.006)	(3.05)	(0.493)	(0.006)	(0.518)	(0.274)	(0.005)	(0.182)	(0.129)
Cattle Density	0.741	-17.7**	-17.7**	4.99*	-69.0**	-62.6*	-0.110	15.3***	20.1**
	(1.18)	(8.16)	(9.00)	(2.55)	(33.2)	(32.7)	(1.12)	(3.19)	(7.91)
Dependent Variable:	Gross forest-like vegetation loss all								
Pasture Gain	0.906***	1.04***	1.10***	0.895***	1.07***	1.18***	0.859***	1.02***	1.04***
	(0.020)	(0.185)	(0.219)	(0.021)	(0.183)	(0.264)	(0.024)	(0.045)	(0.042)
Cattle	0.021***	1.46	0.549	0.017***	0.618	0.392	0.014***	0.554***	0.429***
	(0.005)	(2.18)	(0.392)	(0.005)	(0.453)	(0.239)	(0.005)	(0.165)	(0.110)
Cattle Density	-1.74	18.7**	17.9**	-5.48**	55.7*	49.5*	-0.958	-18.1***	-23.7***
	(1.45)	(8.65)	(9.01)	(2.71)	(28.8)	(27.6)	(1.63)	(3.14)	(8.81)
Dependent Variable:	Gross forest loss all								
Pasture Gain	0.855***	1.22***	1.32***	0.852***	1.16***	1.30***	0.807***	0.884***	0.892***
	(0.028)	(0.346)	(0.423)	(0.030)	(0.282)	(0.406)	(0.037)	(0.042)	(0.036)
Cattle	0.020***	1.54	0.544	0.016***	0.597	0.355	0.013***	0.465***	0.350***
	(0.005)	(2.32)	(0.401)	(0.005)	(0.453)	(0.242)	(0.005)	(0.163)	(0.115)
Cattle Density	-1.16	15.8**	15.2*	-5.17**	56.4*	50.5*	-0.231	-14.8***	-19.4**
	(1.17)	(7.45)	(7.85)	(2.59)	(28.8)	(27.8)	(1.19)	(2.95)	(7.52)
Fixed-effects									
muni_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
State-year FEs	No	No	No	Yes	Yes	Yes	No	No	No
Muni-specific trends	No	No	No	No	No	No	Yes	Yes	Yes
Fit statistics									
Observations	31,480	31,480	31,480	31,480	31,480	31,480	31,480	31,480	31,480
F-test, Pasture		113.49	147.26		97.010	113.54		758.96	1,013.8
F-test, Pasture Gain		54.109	48.232		71.643	50.614		432.97	547.34
F-test, Cattle		1.2581	9.8736		11.902	30.924		32.519	65.782
F-test, Cattle Density		566.92	846.87		573.72	806.05		843.47	751.08

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the whole period (2003–2022), using OLS in columns (1), (4) and (7), the IV specification in the other columns for all municipalities in the Cerrado, the Amazon and the Pantanal biomes. Models in columns (2), (5), and (8) use the instrument based on the shares as specified in Equation 5, models in columns (3), (6) and (9) alternatively use municipality i's initial share on total pasture, share on total cattle head stock or cattle density as share variable for pasture/pasture gain, cattle head and cattle density, respectively. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality fixed effects, models in columns (1) to (3) include year fixed effects, models in columns (4) to (6) include state-year fixed effects, models in columns (7) to (9) include a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

Table C3: Regression results for Legal Amazon

Model:	OLS (1)	IV-int (2)	IV-share (3)	OLS (4)	IV-int (5)	IV-share (6)	OLS (7)	IV-int (8)	IV-share (9)
Dependent Variable:	Difference in forest-like vegetation cover								
Pasture	-0.770***	-0.909***	-0.810***	-0.762***	-1.08***	-0.951***	-0.728***	-0.905***	-0.832***
	(0.035)	(0.089)	(0.110)	(0.038)	(0.096)	(0.099)	(0.042)	(0.080)	(0.071)
Cattle	-0.030***	-0.701*	-0.482**	-0.025***	-0.991*	-0.608*	-0.020***	-0.623***	-0.537***
	(0.008)	(0.371)	(0.242)	(0.008)	(0.548)	(0.311)	(0.007)	(0.147)	(0.117)
Cattle Density	2.84	-34.3**	-34.0**	5.68**	-67.0**	-59.8*	1.68	32.7***	42.0***
	(2.49)	(15.0)	(16.6)	(2.52)	(33.1)	(32.0)	(2.54)	(5.59)	(14.7)
Dependent Variable:	Difference in forest cover								
Pasture	-0.721***	-0.797***	-0.730***	-0.715***	-0.894***	-0.804***	-0.676***	-0.752***	-0.701***
	(0.043)	(0.149)	(0.139)	(0.045)	(0.144)	(0.140)	(0.051)	(0.081)	(0.074)
Cattle	-0.029***	-0.591	-0.409*	-0.025***	-0.792	-0.486	-0.020***	-0.508***	-0.439***
	(0.008)	(0.359)	(0.236)	(0.008)	(0.518)	(0.304)	(0.007)	(0.147)	(0.116)
Cattle Density	1.90	-29.2**	-29.3**	4.82*	-70.1**	-63.4*	0.235	27.7***	36.4***
	(2.16)	(13.4)	(14.9)	(2.47)	(34.0)	(33.2)	(2.00)	(5.46)	(13.8)
Dependent Variable:	Gross forest-like vegetation loss all								
Pasture Gain	0.918***	0.756***	0.761***	0.907***	0.849***	0.879***	0.870***	0.956***	0.963***
	(0.020)	(0.188)	(0.165)	(0.021)	(0.134)	(0.108)	(0.024)	(0.030)	(0.029)
Cattle	0.025***	0.426	0.277	0.022***	0.681	0.408	0.017***	0.474***	0.412***
	(0.007)	(0.337)	(0.221)	(0.007)	(0.465)	(0.273)	(0.006)	(0.130)	(0.102)
Cattle Density	-3.11	30.9**	30.2**	-5.27**	56.9*	50.4*	-1.79	-31.3***	-40.9***
	(2.42)	(13.9)	(15.0)	(2.64)	(29.5)	(28.1)	(2.57)	(5.18)	(14.9)
Dependent Variable:	Gross forest loss all								
Pasture Gain	0.879***	0.817***	0.846***	0.875***	0.827***	0.858***	0.828***	0.916***	0.920***
	(0.027)	(0.157)	(0.129)	(0.028)	(0.150)	(0.121)	(0.035)	(0.028)	(0.028)
Cattle	0.025***	0.440	0.289	0.022***	0.646	0.382	0.017***	0.448***	0.386***
	(0.007)	(0.331)	(0.217)	(0.007)	(0.463)	(0.273)	(0.006)	(0.133)	(0.104)
Cattle Density	-2.37	26.6**	26.1*	-4.93**	57.8*	51.5*	-0.770	-27.0***	-35.4***
	(2.15)	(12.3)	(13.3)	(2.50)	(29.5)	(28.4)	(2.09)	(5.01)	(13.3)
Fixed-effects									
muni_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
State-year FEs	No	No	No	Yes	Yes	Yes	No	No	No
Muni-specific trends	No	No	No	No	No	No	Yes	Yes	Yes
Fit statistics									
Observations	16,160	16,160	16,160	16,160	16,160	16,160	16,160	16,160	16,160
F-test, Pasture		181.84	210.29		136.77	160.96		577.53	758.12
F-test, Pasture Gain		132.54	104.08		152.33	117.68		486.96	542.56
F-test, Cattle		24.592	46.664		13.780	33.986		62.516	88.673
F-test, Cattle Density		288.82	431.74		293.68	412.71		432.84	385.50

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the whole period (2003–2022), using OLS in columns (1), (4) and (7), the IV specification in the other columns for all municipalities in the states comprising the Legal Amazon. Models in columns (2), (5), and (8) use the instrument based on the shares as specified in Equation 5, models in columns (3), (6) and (9) alternatively use municipality i's initial share on total pasture, share on total cattle head stock or cattle density as share variable for pasture/pasture gain, cattle head and cattle density, respectively. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality fixed effects, models in columns (1) to (3) include year fixed effects, models in columns (4) to (6) include state-year fixed effects, models in columns (7) to (9) include a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

D Heterogeneity Analysis

D1 Biome-specific results

Table D1: Biome-specific regression results

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Amazon Biome					
Dependent Variable:	Δ forest-like vegetation cover		Δ forest cover			
Pasture	-0.908***	-0.932***	-0.732***	-0.788***		
	(0.075)	(0.084)	(0.163)	(0.074)		
Cattle	-1.05*	-0.737***	-0.854*	-0.620***		
	(0.554)	(0.173)	(0.516)	(0.158)		
Cattle Density	-53.8**	49.2***	-51.9**	47.9***		
	(23.1)	(8.43)	(22.6)	(8.41)		
Fit statistics						
Observations	10,060	10,060	10,060	10,060		
F-test, Pasture	165.89	438.62	165.89	438.62		
F-test, Cattle	9.1950	33.854	9.1950	33.854		
F-test, Cattle Density	180.42	272.81	180.42	272.81		
	Cerrado Biome					
Dependent Variable:	Δ forest-like vegetation cover		Δ forest cover		Δ savanna cover	
Pasture	0.602	-1.14***	-0.136	-0.089	-0.116	-0.359***
	(0.776)	(0.183)	(0.160)	(0.088)	(0.101)	(0.139)
Cattle	0.375	-2.31	-0.101	-0.155	-0.027	-0.727
	(0.374)	(4.17)	(0.192)	(0.353)	(0.088)	(1.30)
Cattle Density	81.1	-849.7	-578.1	-789.3	1,125.5**	296.9
	(477.3)	(718.7)	(394.2)	(499.2)	(503.6)	(367.0)
Fit statistics						
Observations	21,240	21,240	21,240	21,240	21,240	21,240
F-test, Pasture	56.955	275.98	56.955	275.98	56.955	275.98
F-test, Cattle	4.5191	1.4342	4.5191	1.4342	4.5191	1.4342
F-test, Cattle Density	18.146	12.320	18.146	12.320	18.146	12.320
Fixed-effects						
muni_id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Muni-specific trends	No	Yes	No	Yes	No	Yes

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the whole period (2003–2022), using OLS in columns (1) and (4) the IV specification in the other columns for all municipalities in the Amazon biome (upper panel) and Cerrado biome (lower panel). Models in columns (2) and (5), use the instrument based on the shares as specified in Equation 5, models in columns (3) and (6) alternatively use municipality i's initial share on total pasture, share on total cattle head stock or cattle density as share variable for pasture/pasture gain, cattle head and cattle density, respectively. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality fixed effects, models in columns (1) to (3) include year fixed effects, models in columns (7) to (9) additionally include a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

D2 Period-specific results

Table D2: Regression results for post-2015 period

Model:	OLS (1)	IV-int (2)	IV-exp (3)	OLS (4)	IV-int (5)	IV-exp (6)
	Biomes Amazon, Cerrado & Pantanal					
Dependent Variable:	Difference in forest-like vegetation cover					
Pasture	-0.580***	-1.20***	-0.889***	-0.552***	-0.904***	-0.669***
	(0.051)	(0.300)	(0.149)	(0.054)	(0.254)	(0.091)
Cattle	-0.001	-0.955	-0.010	-0.006	0.439	-0.055**
	(0.007)	(1.22)	(0.031)	(0.005)	(0.897)	(0.024)
Cattle Density	-2.90***	546.1	-2.91***	-2.39**	-22.6	-3.78***
	(0.696)	(1,224.9)	(0.989)	(0.946)	(17.6)	(1.18)
Dependent Variable:	Difference in forest cover					
Pasture	-0.516***	-0.685***	-0.640***	-0.482***	-0.785***	-0.571***
	(0.057)	(0.262)	(0.114)	(0.063)	(0.251)	(0.120)
Cattle	-0.001	-0.580	0.005	-0.005	0.326	-0.057***
	(0.006)	(0.742)	(0.031)	(0.005)	(0.662)	(0.021)
Cattle Density	-1.96	79.1	-1.59	-2.22***	-41.3	-3.83*
	(1.32)	(195.6)	(1.03)	(0.555)	(30.3)	(1.97)
Fit statistics						
Observations	11,018	11,018	11,018	11,018	11,018	11,018
F-test (1st stage), Pasture		44.089	62.434		70.674	98.706
F-test (1st stage), Cattle		4.5179	68.639		3.6725	65.528
F-test (1st stage), Cattle Density		0.29784	7,795.6		62.733	6,989.4
	Legal Amazon					
Dependent Variable:	Difference in forest-like vegetation cover					
Pasture	-0.624***	-0.496	-0.558***	-0.601***	-0.706***	-0.652***
	(0.056)	(0.340)	(0.090)	(0.059)	(0.089)	(0.099)
Cattle	-0.004	-0.225	-0.034	-0.006	10.4	-0.079**
	(0.008)	(0.194)	(0.041)	(0.006)	(298.8)	(0.039)
Cattle Density	-2.74***	297.8	-2.62*	-3.83***	-50.4	-6.48**
	(0.943)	(658.9)	(1.46)	(1.13)	(38.5)	(2.62)
Dependent Variable:	Difference in forest cover					
Pasture	-0.576***	-0.499	-0.519***	-0.538***	-0.605***	-0.632***
	(0.062)	(0.310)	(0.098)	(0.070)	(0.115)	(0.125)
Cattle	-0.003	-0.208	-0.012	-0.006	7.62	-0.072**
	(0.008)	(0.184)	(0.042)	(0.006)	(218.5)	(0.030)
Cattle Density	-2.39	-0.462	-2.16	-3.70***	-70.9	-6.65*
	(1.49)	(109.6)	(1.52)	(0.779)	(52.8)	(3.59)
Fit statistics						
Observations	5,656	5,656	5,656	5,656	5,656	5,656
F-test (1st stage), Pasture		42.347	76.372		161.21	81.956
F-test (1st stage), Cattle		25.617	36.949		0.01280	19.726
F-test (1st stage), Cattle Density		0.16655	3,991.8		31.623	3,511.0
Fixed-effects						
muni_id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-specific trends	No	No	No	Yes	Yes	Yes

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the post-2015 period (2016–2022), using OLS in columns (1) and (4) and the IV specification in the other columns for all municipalities in the Cerrado, the Amazon and the Pantanal biomes (upper panel) and the Legal Amazon (lower panel). Models in columns (2) and (5) use the instrument based on the shares as specified in Equation 5, models in columns (3) and (6) alternatively use the instrument based on the shares as specified in Equation 6. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality and time fixed effects, models in columns (4) to (6) additionally include a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.

E Robustness checks

Table E1: Regression results for robustness checks

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Biomes Amazon, Cerrado & Pantanal Biome							
Dependent Variable:	Δ forest-like vegetation cover				Δ forest cover			
Pasture	-0.981***	-0.880***	-0.895***	-0.972***	-0.580***	-0.674***	-0.504***	-0.655***
	(0.065)	(0.075)	(0.061)	(0.075)	(0.118)	(0.098)	(0.124)	(0.118)
Cattle	-0.888***	-0.821***	0.549**	-1.19***	-0.533***	-0.622***	0.307	-0.791***
	(0.267)	(0.281)	(0.251)	(0.382)	(0.182)	(0.224)	(0.207)	(0.260)
Cattle Density	20.3***	512.2	11.3***	3.05**	15.3***	639.2	8.04***	26.1***
	(3.36)	(981.2)	(2.26)	(1.45)	(3.19)	(1,313.5)	(2.13)	(4.29)
Fit statistics								
Observations	31,480	16,860	31,480	31,480	31,480	16,860	31,480	31,480
F-test, Pasture	758.96	566.53	497.12	1,240.4	758.96	566.53	497.12	1,240.4
F-test, Cattle	32.519	23.607	47.467	27.541	32.519	23.607	47.467	27.541
F-test, Cattle Density	843.47	29.820	951.41	808.56	843.47	29.820	951.41	808.56
	Legal Amazon							
Dependent Variable:	Δ forest-like vegetation cover				Δ forest cover			
Pasture	-0.905***	-0.882***	-0.909***	-0.956***	-0.752***	-0.727***	-0.741***	-0.810***
	(0.080)	(0.078)	(0.067)	(0.095)	(0.081)	(0.086)	(0.077)	(0.090)
Cattle	-0.623***	-0.712***	1.82	-0.837***	-0.508***	-0.579***	1.45	-0.688***
	(0.147)	(0.159)	(2.14)	(0.190)	(0.147)	(0.151)	(1.79)	(0.186)
Cattle Density	32.7***	593.5	20.8***	45.1***	27.7***	724.3	16.8***	42.0***
	(5.59)	(1,169.4)	(4.32)	(7.00)	(5.46)	(1,508.7)	(4.09)	(6.89)
Fit statistics								
Observations	16,160	12,660	16,160	16,160	16,160	12,660	16,160	16,160
F-test, Pasture	577.53	600.65	328.64	939.76	577.53	600.65	328.64	939.76
F-test, Cattle	62.516	45.144	4.2422	56.052	62.516	45.144	4.2422	56.052
F-test, Cattle Density	432.84	22.360	486.75	415.00	432.84	22.360	486.75	415.00
Fixed-effects								
muni_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muni-specific trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (muni_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table shows results for estimation of Equation 1 for the whole period (2003–2022), using the IV specification for municipalities in the Amazon, Cerrado, or Pantanal biome (upper panel) and Legal Amazon (lower panel). Models in columns (1) and (5) show results for the baseline specification. Models in columns (2) and (6) show results for municipalities with forest cover larger than 10% in 2002 and forest loss until 2022. Models in columns (3) and (7) show results with the instrument $B_{i,t}$ entering equation 3 in unlagged form. Models in columns (4) and (8) show results with the measure for pasture/cattle expansion $c_{i,t}$ entering equation 1 in lagged form. All models include information on GDP per capita, population, the share of indigenous areas on total land area, an indicator for dry spells as well as the lagged number of environmental fines, lagged agricultural price indices, and lagged forest area. All variables except the indicator for dry spells, lagged forest cover and cattle density enter the models in first differences. All models include municipality fixed effects, year fixed effects and a municipality-specific linear time trend. Standard errors are clustered at the municipality level. F-tests report the F-statistics of the first stage for IV specifications.