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YSSP Report

Young Scientist Summer Program

Mining, land use, and regional income in Brazil: Economic and environmental perspectives on resource-dependent development.

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ABSTRACT

The question if natural resource abundance translates into higher incomes in the regions where and close to where the extraction takes place is an empirical one. This paper examines the local economic effects of mining and land use change for Brazil, where the government is currently on the verge of opening indigenous and protected land for industrial mining, in particular in the Amazon region, arguing that economic stimulus from extractive industries would outweigh environmental and social concerns. In order to challenge this claim, we employ a panel-structure spatial growth model at the level of municipalities for the years 2005-2013. Identification of effects is attained exploiting granular geographical data on land cover and the locations of mines, as well as socio-economic determinants of economic growth for 5,249 Brazilian municipalities. Our empirical framework further considers spatial autocorrelation and allows for the assessment of spillover effects between municipalities. Results indicate that the local economic effects of mining activities are ambivalent, depending also on external global factors such as demand for commodities and their prices. For the period previous to 2010, we find positive effects on GDP growth, directly and via spatial spillovers to neighbouring municipalities. After 2010, the direct effect fades and the spillover effects become negative. We then investigate potential negative environmental downturns, adapting our model for explaining forest loss. Our findings show that mining is associated with accelerating deforestation, also via substantial spatial spillovers. We conclude that extractive industries may stimulate local economies, but there is a trade-off between economic and environmental spheres of natural resource extraction. This trade-off fades during less favourable global market conditions, as regional economic growth from mining disappears, while negative environmental impacts remain.

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1 Introduction

The conditions under which, and if at all, resource abundance effects the economic development of countries has been of scholarly concern for a long time. Empirical evidence suggests that resource wealth did often not translate into economic prosperity, and many countries well-endowed with natural resources showed lower growth rates than resource-poor economies and were prone to economic instability. Auty (1993) coined the debates about this phenomenon, introducing the 'resource curse thesis', which was followed up and extended by other scholars such as Sachs and Warner (1995, 2001) and Humphreys et al. (2007). They argue that resource wealth often hinders economic growth due to a number of of channels that contribute to a 'crowding-out logic' (Sachs and Warner 2001), where the availability of natural resources expels other sectors important for sustained growth such as manufacturing, education and health. Further causes are rent-seeking and possible corruption of political elites and dependence on international markets and commodity prices, which can be fatal to economies lacking sector diversification.

While the early resource curse literature is mostly focused at the level of countries, a more recent strand of literature is concerned with subnational socioeconomic dynamics of extractive industries. This level of analysis offers a new perspective on the resource curse (Manzano and Gutiérrez 2019), but also a number of arguments that mining can, via backward linkages such as via market mechanisms and local spillovers, stimulate regional economic development (Aragón and Rud 2013; Arias et al. 2013; Aragón et al. 2015).

Brazil is a characteristic example for the resource curse thesis. Due to its abundance of land and mineral resources, the country experienced only slow maturation of its manufacturing subsectors in the second half of the twentieth century (Auty 1995). Having its economy closely tied to global commodity markets led to considerable economic growth during the 2000s commodities boom, but intensified primary resource extraction also led to the fragmentation and degradation of ecosystems and natural livelihoods, and ended in economic and political difficulties as soon as commodity prices began to fall. And still, this historic record did not prevent the idea of resource-dependent development from being fiercely debated in Brazil today. While the current government strongly promotes a liberalisation of access to land and resource deposits for agriculture and extractive industries, opponents constantly issue warnings highlighting the threat of such practice for the environment and the country's indigenous communities (e.g. Siqueira-Gay et al. 2020; Rorato et al. 2020). The links between mining and other land use change and regional economic growth, however, remained empirically unchallenged.

Leaving the role of land use and extractive industries for a moment aside, the most common way to conduct larger-sample empirical studies on the determinants of economic growth is to employ growth regressions as advocated by Barro (1991). Building on neoclassical growth theory (Solow 1956; Mankiw et al. 1992), Barro (1991) suggests an econometric framework where observed economic growth rates are conditioned on initial capital formation as well as further growth determinants derived from endogenous growth theory such as human capital and research and development (Lucas 1988; Romer 1990). During the past three decades, an extensive body of literature using growth regressions has emerged and, similar to the resource curse literature, the focus of growth regression studies has more recently shifted to conducting regional analyses. With regional studies becoming more common, scholars also recognised the need for improved methods in order to account for spatial autocorrelation in the observations and to evaluate spillover effects (e.g. Ertur and Koch 2007; LeSage and Fischer 2008). For Brazil, early subnational assessments of economic growth were performed by Azzoni (2001) at the regional and state level. Municipality-level growth studies for Brazil were performed by Resende (2011; 2013). They were refined with a spatial econometric framework (Cravo and Resende 2013; Resende et al. 2016), and exploit information from an increasing amount of explanatory variables as compared to early growth regressions. However, to date, no economic growth study building on an econometric framework considers Brazil's wealth of land area and natural resources such as iron and gold ores as important factors for local economies.

In this paper, we connect the two strands of literature – perspectives on the role of natural resources for economic development and applied macroeconometric works –, both of which have shifted their interest from nation-wide analyses and comparisons to local impacts and regional links. We chose to specifically investigate the Brazilian case for three reasons: the substantial size of its primary sector exports and the large scale of industrialisation of its mining and agriculture sectors, the political relevance given that powerful political forces urge for an intensification of resource-dependent development strategies, and the potential cost of resource development, given the exceptional role of indigenous populations, the Amazon rain forest, and the vast biodiversity in large parts of Brazil.

The objectives of this study are threefold. First, we aim to identify and quantify the economic effects of mining and of other types of land use change, such as the transformation from natural forests to cropland, at the regional level. We consider municipalities, representing the most granular political entities in Brazil, as observational units. Second, we assess the spatial transmission of impacts. The spatial dimension of economic activity was demonstrated in previous studies, showing that spatial dependence is a robust feature of regional economic growth (e.g. LeSage and Fischer 2008). But what does this mean for natural resource extraction? Manzano and Gutiérrez (2019) propose that also non-producing areas may be affected due to spillover effects and the decentralisation of revenues. The question is tightly related to debates about the presence of either enclave economies, where extraction sites are economically isolated from their surroundings, or clusters, where strong links to proximate regions induce positive economic stimulus, for instance via local procurement and employment creation (Arias et al. 2013). The third objective is to deliver information about potential trade-offs between resource-led economic growth and negative environmental consequences. This is especially relevant for policymakers, who have to decide about legal frameworks considering economic, environmental and social outcomes. In order to do so, we investigate the deforestation effects of extractive industries as a direct measure of environmental consequences.

All three objectives are achieved utilising panel-structure spatial econometric models for the time period 2005-2013, which we estimate using Bayesian techniques. We regress 5-year average annual GDP growth rates on well-established determinants of economic growth, augmented with land cover information and the location of mines and repeat this step in a second model designed to assess forest loss effects. For both models, we make use of a novel georeferenced data set using yearly data from various sources, which are obtained at or aggregated to the municipality level. A unique feature of this study is our approach of how to identify location and opening years of mines, where we combine recent data on the area occupied by mining with high-resolution vegetation time series from satellite imagery.

Our results suggest that the local economic effects of mining activities in Brazil are mixed. Before 2010, when commodity prices were rapidly rising, mining activities directly induced 3.8% higher GDP growth as compared to the Brazilian average and another 4.6% due to spillover effects. Since 2010, however, there was no sign for direct economic stimulus due to mining. Furthermore, we find that mining operations negatively affected the growth rates of neighbouring municipalities by 1.8% between 2010 and 2013. We also find that economic growth was induced by the transformation of land for agricultural use. Negative GDP growth spillovers were, however, observed from clearing natural forest for agriculture or pasture. Finally, our results show that mining was associated with accelerating deforestation, especially via substantial spatial spillovers. The findings hence suggest that there is a trade-off between economic and environmental effects. The nature of trade-off, however, altered in more recent years, where global commodity prices and hence overall economic conditions in Brazil worsened and economic effects faded out, while environmental concerns remained.

The study and its results offer two main contributions to the literature. First, there is little empirical indication for Brazil and elsewhere how mining activities and land use change relate to *local economic growth*. Recent studies on local socioeconomic impacts of mining in Brazil relate to single mining projects and rely on field work and household surveys, focusing on local communities' acceptance of mining companies and their operations (Cruz et al. 2020) and their overall socioeconomic situations (Matlaba et al. 2019). Da Silva et al. (2021) go beyond single case studies of mines and consider a sample of 33 mining municipalities in order to assess the economic resilience of mining-dependent economies. We directly connect to the debates on whether to expand resource extraction in Brazil and elsewhere. Especially those in favour of resource-led development tend to rely on a simplistic development narrative (Hope 2019). We hence present urgently needed insights about the links between natural resource wealth and regional development. In this study, we cover economic perspectives, but also introduce an analysis on the deforestation effects of extraction and land use for a more holistic understanding of development. Besides the spatial structure, this involves a careful consideration of global market conditions.

Second, municipality-level, large-n economic growth studies for Brazil have been limited to the works of Guilherme Mendes Resende and colleagues (Resende 2011; Resende 2013; Cravo and Resende 2013; Resende et al. 2016). Our study extends this literature by utilising data that is yearly (instead of census data, which was only available for 1970, 1980, 1991 and 2000) and for a more recent time period. On top of that, this paper addresses the spatial dependence between municipalities, which was rarely considered in past studies.

The remainder of this paper is organised as follows. In the next section, we provide a brief historic overview about resource-dependent economic growth in Brazil and related challenges, followed by the empirical framework and the data in Sections 3 and 4. Results are presented and discussed in Section 5. Section 6 concludes.

2 Natural resources, economic growth and crisis in Brazil

The economic exploitation of abundant Brazilian land and mineral resources has a long history, starting with the arrival of the Portuguese in 1500 and their obsession with finding precious metals and gems. First economic cycles, however, were due to redwood explorations, sugar production, as well as cattle and grazing (Machado and de M. Figueirôa 2001). Rich and economically feasible gold deposits were only discovered at the end of the 17th century. In today's Minas Gerais, gold and later also diamond mining led to increasing prosperity and incredible wealth for the Portuguese crown (ibid.). Substantial agricultural expansion and thus appropriation and utilisation of vast areas of land started in the 19th century. First large-scale plantations were established for coffee production in 1835, shortly after Brazil had gained its formal independence from Portugal, followed by the emergence of rubber production in the Amazon in the 19th century (ibid.).

Today, the formal Brazilian mining sector is highly industrialised, with a focus on the extraction of iron ore, gold, copper and bauxite. While Minas Gerais is still the centre of Brazilian mining, large-scale projects were also established in the North Region, such as the Carajás iron ore mining complex or the Paragominas bauxite mine, both in Pará. Agriculture and pasture dominate land use in the south. Leading in national grain production and a hot spot of agricultural expansion is Mato Grosso in the Central-West, where mostly soybean, corn, cotton and sugarcane are produced.

The practice of large-scale plantation management and the expansion of pasture for cattle ranching had far-reaching environmental consequences (Soterroni et al. 2018). As a reaction, environmental, biodiversity and especially forest conservation concerns were given rise in the early 2000s, when Brazilian deforestation rates reached exceptionally high numbers. In order to steer against environmental degradation, the political administrations under the presidents Cardoso (1995-2002) and Lula (2003-2010) and other stakeholders adopted a number of policies, oriented towards better monitoring systems, expansion of protected areas and stricter law enforcement (ibid.). The measures included increased Legal Reserve requirements in the Brazilian Forest Code, compelling landowners to retain larger shares of their properties as natural land (van der Hoff and Rajão 2020), as well as the Amazon Soy Moratorium in 2006, an agreement by grain traders ensuring that soy production in the Amazon region would not occur on recently deforested land (Heilmayr et al. 2020).

Relative to other resource-rich South American countries, the Brazilian economy is considered diversified, with intact domestic manufacturing and service sectors. However, other than the Global North and some South East Asian economies, Brazil is still strongly dependent on its primary sector and the export of unprocessed raw materials. Since the mid-20th century, this dependence has caused slow industrialisation and high socioeconomic inequalities (Auty 1995), but also economic impetus as long as global demand for raw materials kept increasing. Comparing the country's GDP per capita over the past two decades with global commodity prices (Figure 1) reveals that Brazil has experienced economic expansion between 2000 and 2013, with only a short interruption during the global financial crisis in 2008. During most of the same time, there was a rise in global commodity prices known as the 2000s commodities boom. After having recovered from the global financial crisis,

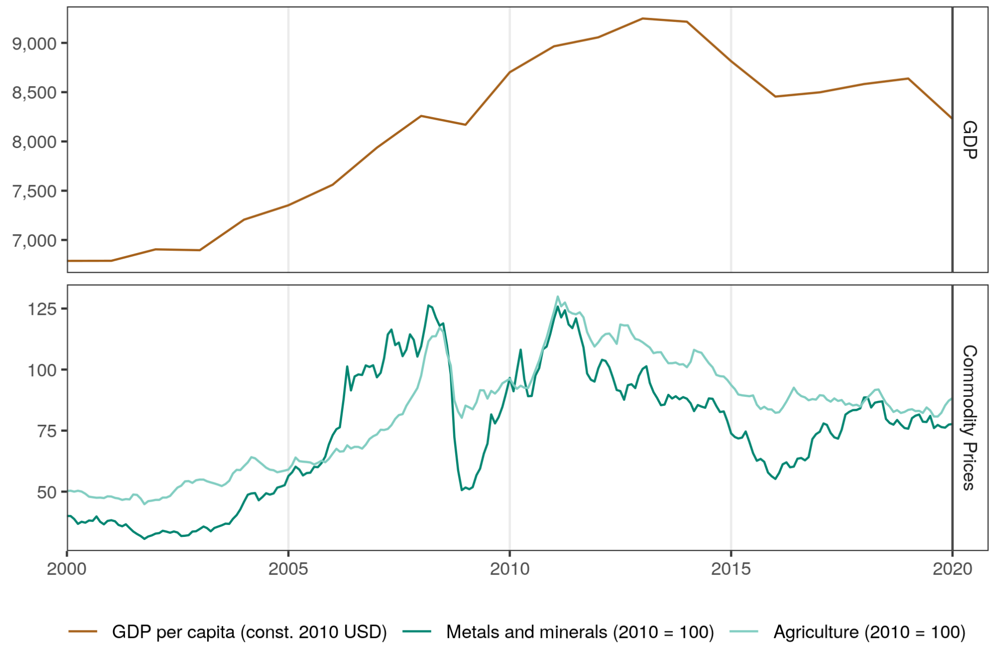


Figure 1: Brazilian GDP per capita and global commodity price indices. Sources: World Bank 2021a, 2021b.

commodity prices fell steadily between 2011 and 2016. Low commodity prices and declining demand for Brazilian commodities – especially from China – hit the country hard, peaking in deep recession: the 2014 Brazilian economic crisis.

As a consequence of the economic, but also severe political and social crisis, Lula's successor president Dilma Rousseff was impeached and removed from office in 2016. After two years of Michel Temer serving as head of state, Jair Bolsonaro was elected president in 2018. The Temer and Bolsonaro governments mark a distinct change in the country's environmental and natural resource governance, implying also a turnaround regarding tropical rain forest preservation strategies of the former governments (de Area Leão Pereira et al. 2019; Escobar 2020). The new agenda targets an intensification of commodity production and exports and promotes resource-led development via acts of environmental deregulation. The PL 191-2020 bill signed in 2020, for instance, is meant to facilitate access to land for natural resource extraction, having severe implications for indigenous communities and their livelihoods (Siqueira-Gay et al. 2020; Rorato et al. 2020).

Brazil therefore serves as a very relevant case for investigating the effects of extractive activities and land use change on both the economy and the environment, which we consider equally relevant for a broader understanding of *development*. On the one hand, Brazil experienced both growth and decline tied to its wealth in natural resources, and on the other hand there is strong evidence that the exploitation thereof harmfully interferes with ecosystems and communities. This observation supports Manzano and Gutiérrez (2019) stating that "[t]he policy debate on resource-rich countries needs to move beyond this simple dichotomy of curses and blessings" (p.262). We argue that investigating the resource-environment-economy nexus requires the consideration of spatial and temporal contexts. We therefore introduce our approach to modelling economic and environmental impacts of mining and other land use change in the next section.

3 Empirical design

In order to explain the economic growth rates of municipalities with a focus on mining and land use change effects, we follow the well-established concept of growth regressions. The basic idea of this empirical research strategy is to regress growth rates of countries or regions on their capital stock (usually GDP) at the initial period of a certain growth window as well as a number of further determinants of growth (Barro 1991). Typically, these include information on population growth, human capital stock and sectoral structure such as gross value added or employment in various economic sectors (e.g. LeSage and Fischer 2008; Crespo Cuaresma et al. 2014).

The study furthermore adapts a spatial econometric approach. Spatial econometrics traces back to the work of Paelinck and Klaassen (1979) and has been subject to extensive methodological advancements since then, leading to applied contributions in economics, environmental, and other social sciences. Spatial models explicitly consider the non-randomness of observations across space, addressing the bias and misleading inference that may result from spatial dependence (Baltagi and Pirotte 2010). Several studies found strong evidence that regions are not independent, i.e. regional economic growth exhibits spatial autocorrelation (e.g. López-Bazo et al. 2004; LeSage and Fischer 2008; Crespo Cuaresma et al. 2014), which is shown to be especially strong for smaller Brazilian regions (Resende et al. 2016). One possible cause for the observed spatial dependence are unobserved determinants of economic growth that are correlated across regions, such as cultural, institutional and political factors (ibid.).

We employ a panel-structure spatial model. Spatial panel models account for spatial correlations and at the same time offer extended possibilities to consider time- or region-specific idiosyncratic effects (Elhorst 2010). Following Ertur and Koch (2007) and LeSage and Fischer (2008), and in line with the econometric framework in Resende et al. (2016), we employ a panel-structure spatial Durbin model (SDM) in the following form:

$$\boldsymbol{y}_t = \rho \boldsymbol{W} \boldsymbol{y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X}_t \boldsymbol{\theta} + \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Omega}), \ \boldsymbol{\Omega} = \sigma^2 \boldsymbol{I}_n, \tag{1}$$

where $\boldsymbol{y}_t$ denotes an $n \times 1$ vector of regional economic growth rates. As advocated by Caselli et al. (1996), we use five-year periods as growth windows in order to smooth over short-term business cycle influences and calculate the respective average annual growth rates $\boldsymbol{y}_t = [ln(\boldsymbol{Y}_{t+5}) - ln(\boldsymbol{Y}_t)]/5 * 100$, with $\boldsymbol{Y}_t$ denoting per capita GDP levels at time t. $\boldsymbol{X}_t$ is an $n \times k$ matrix of k exogenous country characteristics in the initial period. These include prominent determinants of economic growth such as income, population density, education and indicators for industrial structure, but also information on mining activities, land use and land use change. In order to allow for a distinction between mining effects previous to 2010 and since then, we interact the binary mining indicator with respective dummy variables. We chose 2010 as the year of separation, following insights from Figure 1 that the past two decades show a rise and fall in both Brazilian GDP and global commodity prices, as well as an explorative approach running the model for all possible combinations of sample periods without interaction term (see Appendix B). $\boldsymbol{W}$ is an $n \times n$, non-negative, row-standardised spatial weights matrix. Its elements are used to impose a structure of spatial dependence upon observational units, setting $w_{ii} = 0$ and $w_{ij} > 0$ if regions i and j are defined as neighbours ($i, j = 1, \ldots, n$). Characteristically for an SDM, the regression equation includes the spatially-lagged dependent variable $\boldsymbol{W}\boldsymbol{y}_t$ as well as the spatially-lagged regional characteristics $\boldsymbol{W}\boldsymbol{X}_t$ as explanatory variables. The $k \times 1$ vectors of unknown parameters $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ correspond to $\boldsymbol{X}_t$ and $\boldsymbol{W}\boldsymbol{X}_t$ respectively and ρ (having stability condition $|\rho| < 1$, which is satisfied by row-standardizing $\boldsymbol{W}$ (LeSage and Pace 2009)) is a scalar parameter measuring the magnitude of spatial autocorrelation. If $\rho = 0$, we obtain a growth regression model with spatial lags in $\boldsymbol{X}$ (SLX), where regional growth rates are independent, but $\boldsymbol{W}\boldsymbol{X}$ is still considered. The model collapeses into a classical linear model in the case where both $\rho = 0$ and $\boldsymbol{\theta} = 0$. Finally, the model considers a time-period-specific constant $\boldsymbol{\xi}_t$, capturing temporal effects such as commodity price dynamics. We estimate the model in a Bayesian fashion, following the standard Markov Chain Monte Carlo (MCMC) estimation framework as proposed for spatial econometrics in LeSage and Pace (2009).

Our second model is designed to assess the effect of mining on forest loss instead of economic growth rates, where we again use municipalities as observation units. Forest loss is expected to be subject to significant spatial spillover (Busch and Ferretti-Gallon 2017; Kuschnig et al. 2021), which is why we employ an SDM just as we do for the growth model described in Equation 1. In the forest loss model, the dependent variable $\boldsymbol{y}_t$ denotes a vector of cleared land within each municipality. For the design matrix $\boldsymbol{X}_t$ we consider almost the same set of variables as for the growth model, because most determinants of economic growth overlap with indicators used for explaining forest loss, such as population density, economic activity and biophysical characteristics (Busch and Ferretti-Gallon 2017). Case studies for the Amazon region suggest that mining was a driver of deforestation, also via substantial indirect effects (Alvarez-Berríos and Aide 2015; Sonter et al. 2017), forming our expectation that we would observe similar effects for the municipality level. All other features of the model remain the same as in the growth specification.

Assuming independence of observations, the estimation coefficients of conventional (non-spatial) linear models can be typically interpreted as marginal changes in the dependent variable due to changes in one of the explanatory variables. In this regard, spatial models require additional steps because we explicitly impose dependence among observations, implying that the partial derivatives of the dependent variable in region i with respect to an explanatory variable in region j are potentially non-zero and therefore cause feedback effects. LeSage and Pace (2009) discuss how to calculate average direct, indirect (i.e. spillover) and total impacts as a solution to this issue: First, transforming Equation 1 to

$$\boldsymbol{y}_t = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}(\boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t), \tag{2}$$

we derive n^2 partial derivatives of a particular explanatory variable k as

$$\frac{\partial y_i}{\partial x_{jk}} = \boldsymbol{S}_k(\boldsymbol{W})_{ij} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}(\boldsymbol{I}_n\beta_k + \boldsymbol{W}\theta_k)_{ij}, \tag{3}$$

where infinite feedback effects are captured through the spatial multiplier $(\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}$. We can then summarise the obtained impact matrix by calculating the average total effect

Variable	Description
Economic growth	Five-year average annual growth rate of gross domestic product per capita. *Source:* IBGE (2021)
Forest loss	Annual change in land area from classified as natural forest to any other land cover classification (ha). *Source:* MapBiomas (2021)
Mining	Presence of mining within municipality, binary indicator. *Source:* own calculations based on Maus et al. (2020) and MODIS (2021)
Land use change ($LUC^{1,2}$)	Land use change from classification LUC^1 to LUC^2 for the classifications natural forest, forest plantation, grassland, agriculture and pasture (5-year average change in ha, log). *Source:* MapBiomas (2021)
Initial natural forest	Share classified as natural forest. *Source:* MapBiomas (2021)
Initial forest plantation	Share classified as forest plantation. *Source:* MapBiomas (2021)
Initial grassland	Share classified as grassland. *Source:* MapBiomas (2021)
Initial agriculture	Share classified as agriculture. *Source:* MapBiomas (2021)
Initial pasture	Share classified as pasture. *Source:* MapBiomas (2021)
Initial income	Per capita gross domestic product (m BRL, current PPP, log). *Source:* IBGE (2021)
Human capital	Education index from 0 (worst) to 1 (best): schooling coverage (pre-school attendance) and quality in elementary school. *Source:* FIRJAN (2018)
Population growth	Population growth rate (%). *Source:* IBGE (2021)
Population density	Population density (thousand per km^2). *Source:* IBGE (2021)
GVA agriculture	Gross value added in agriculture (m BRL, current PPP, log). *Source:* IBGE (2021)
GVA industry	Gross value added in industry (m BRL, current PPP, log). *Source:* IBGE (2021)
GVA services	Gross value added in services (m BRL, current PPP, log). *Source:* IBGE (2021)
Precipitation	Precipitation yearly average (standardised). *Source:* CRU (2021)
Elevation	Average elevation (m). *Source:* USGS (2021)

Table 1: Variables used in the analysis (measured at the beginning of the respective growth/forest loss window).

as the average over all entries in $\boldsymbol{S}_k(\boldsymbol{W})_{ij}$, the average direct effect as the average only considering its main diagonal, and the average indirect effect as the difference between the two. An interpretation of average direct effects is then given by the average response of the dependent to independent variables over the sample of observations and hence similar to regression coefficients from classical linear models. The average spillover can be interpreted as the cumulative average response of a region's dependent variable to a marginal change in an explanatory characteristic in all other regions.

4 Data

We compiled a balanced panel data set for this study, covering 5,249 Brazilian municipalities over the period 2005-2013 (N = 47,241).[1] Data were collected from various sources and, if necessary, aggregated to the municipality-level (see Table 1).

The dependent variable in the growth model is the five-year average annual growth rate of GDP per capita, which is computed from yearly per capita GDP in BRL at current purchasing power parities as reported by the Brazilian Institute for Geography and Statistics (IBGE). In the last year of the panel, 2013, this measure therefore comprises economic growth between 2013 and 2018. We select five-year growth windows as a suitable measure for mid-term economic effects. Short-term effects are of minor interest for growth studies as these do not reflect structural regional patterns but rather business cycles or other shocks. Considering long-term economic growth is constrained by the data set at hand.

In the forest loss model, we define the dependent variable as the land area that was

[1] We aim to provide free download of the data shortly on PANGAEA.

transformed from natural forest to any other land cover classification (annual change in ha). The data is calculated from municipality-level land cover statistics as provided by MapBiomas (2021).

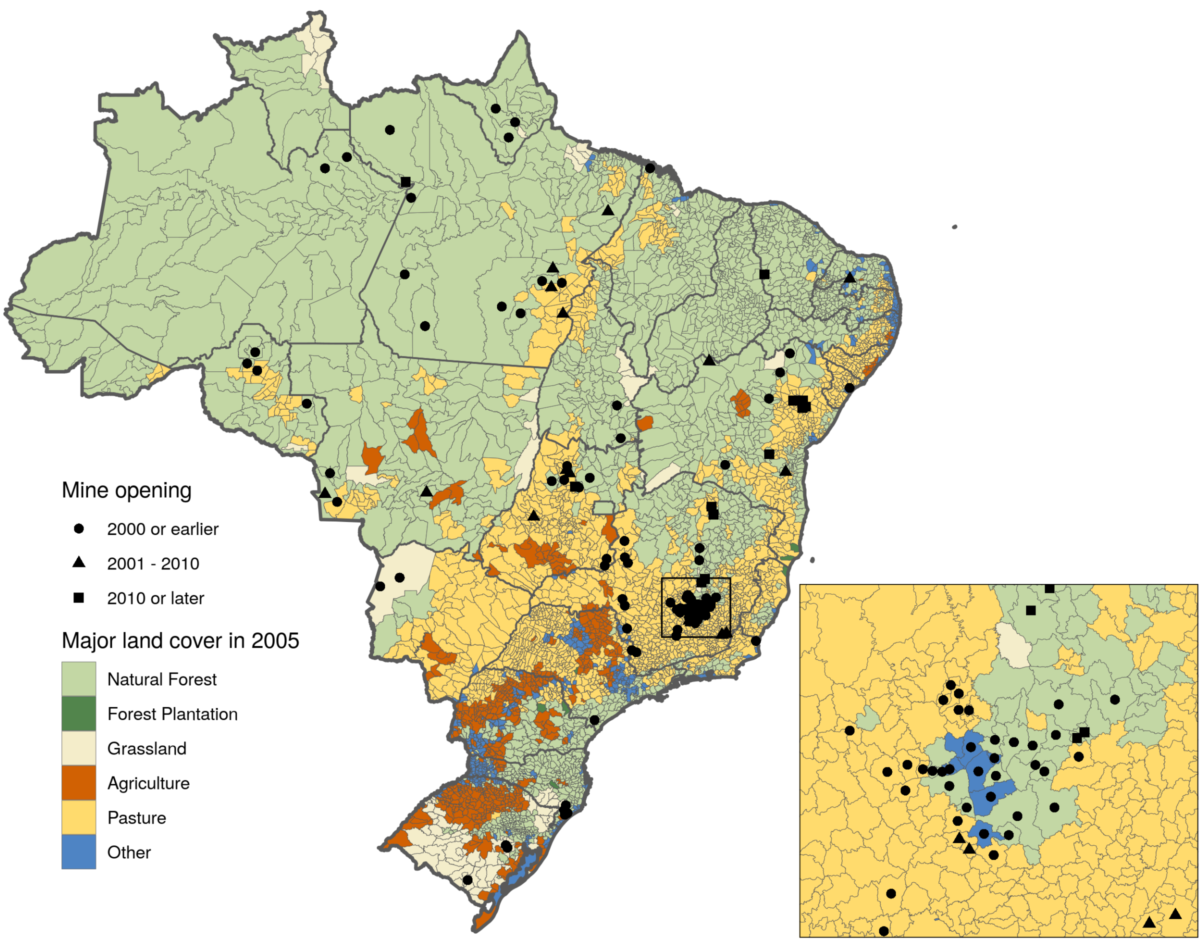


Figure 2: Mining and land use in Brazil. Opening of first mine within municipality (*Source:* own calculations based on Maus et al. 2020 and MODIS 2021) and predominant land cover in 2005, the starting year of the data panel used in this study (*Source:* MapBiomas 2021). Zoom box shows high mine density within the state of Minas Gerais.

The two essential municipality characteristics for this study are (1) the presence of mining and (2) the type and extent of land use change. Figure 2 summarises the locations of municipalities with mines and the main land cover classification per municipality in the starting year of our sample.

Mining enters the models as a binary indicator for the presence of a mine within a municipality in a certain year. In order to construct this indicator, we combine information from two data sources. First, we exploit a recently published global-scale data set indicating the land area that is directly used for mining purposes (Maus et al. 2020). For Brazil, this data set contains 459 polygons in 122 municipalities that add up to 1,500 km^2. The polygons were drawn based on a mosaic of cloudless satellite images "taken during the years 2017 and 2018" (ibid: 3) and therefore only provide a snapshot as of these years. For a proper identification of mining activities since 2005, our panel-structure model requires more temporal detail on the sample period. We therefore utilise the 250 m resolution Normalised Difference Vegetation Index (NDVI) from MODIS (2021) providing information on live green vegetation at 16-day intervals. We compute average NDVI scores for each polygon and then search the time series for the dates of structural breaks in terms of significant negative shocks in the indicator, reasoning that these must be the years when mining activities have started and thus began to effect vegetation. For more detail on the search algorithm and illustrations, see Appendix A.

Limitations of the Maus et al. (2020) data are that they only consider industrial mining and, due to visual interpretation of satellite images, only inform on the locations of mines visible from space (i.e. open pit types), hence inevitably imposing constraints on this study. We therefore focus on the dynamics of industrial, mostly large-scale, mining projects. Omitting informal and artisanal mining, however, should not convey the impression that these would not have economic, environmental and social impacts and we stress the need for better future coverage, starting with more extensive and transparent monitoring and data provision to researchers. The second limitation that underground mining cannot be considered is a negligible issue, because open pit mining is by far the most common in Brazil.[2]

The next key part of this study is that we consider land use change dynamics. Using satellite data on the conversion of land, e.g. from natural forest to pasture or from grassland to agriculture, is an efficient approach for observing economic activity and environmental transformation at the same time. On the one hand, positive economic growth effects can be expected from the additional biomass production that is enabled through land clearings and agricultural expansion as well as – similar to mining – backward linkages to other sectors due to increased purchasing power. On the other hand, land use change is a strong indicator for environmental disruption and often associated with socio-ecological conflicts, which may outweigh economic arguments. Our data is obtained from MapBiomas (2021), providing yearly land transition information from 30 m resolution satellite images aggregated to the level of Brazilian municipalities. We utilise land cover classifications at the first sub-categorical level and consider natural forest and forest plantation for the case of forest, grassland as non forest natural formation, and agriculture and pasture for farming. Other categories such as wetlands, non-vegetated area and bodies of water are omitted since they have minor relevance for analysing land use change at the scope of our analysis. In order to be consistent with the five-year growth horizon of the dependent variable, we computed the average change in hectares over five years. Land use change from any category to natural forest was not considered as a covariate, because it marks a transformation that is only viable over a longer time horizon.

Initial land cover was considered as a proxy for the land cover conditions at the beginning of either a window of GDP growth or a one-year forest loss period. We use data from MapBiomas (2021), again already aggregated to municipalities. In order to reflect the variation in municipality area, this variable enters the models as shares of natural forest, forest plantation, grassland, agriculture and pasture relative to the total municipality area.

[2]Only 11% of active Brazilian mines listed in the SNL Metals and Mining Database (SNL 2021) are reported being predominantly underground.

Figure 2 indicates major land cover classifications per municipality in 2005, the initial year of our sample.

The remaining covariates are control variables and their inclusion is motivated either by economic growth theory and the empirical growth literature, or following Busch and Ferretti-Gallon (2017) for the case of the forest loss model. We consider initial income in terms of per capita GDP in the initial year of a growth window as a proxy for physical capital, which is a major determinant of economic growth in the neoclassical growth framework (Solow 1956) and considered by the majority of economic growth studies as an explanatory variable. A negative relationship between initial stock of physical capital and economic growth, which is explained by diminishing returns to capital accumulation, is a well-established stylised fact in the empirical literature known as the convergence hypothesis (Barro 1991). In addition, a number of studies show that the convergence hypothesis holds for direct impacts in spatial econometric growth frameworks, while spillover effects from the flows of capital, goods, knowledge and people between regions are shown to be positive, implying that poorer regions benefit from having highly capitalised neighbours (e.g. López-Bazo et al. 2004).

Endogenous growth theory highlights the role of human capital as a key driver of innovation processes such as technological change (Lucas 1988; Romer 1990). The direction of indirect effects, however, is uncertain, because positive economic effects from knowledge spillover (Keller 2002) and brain drain channels may counteract each other. We proxy human capital using the FIRJAN (2018) education index, an index for Brazilian municipalities on a scale from 0 (worst) to 1 (best) measuring both schooling coverage and quality. The education index is only available from 2005, constituting the constraint limiting our sample to this starting year.[3]

Population growth is another component from the neoclassical growth framework. According to theory, a positive impact of population growth would hold for absolute income growth at the national scale, but due to capital dilution not for the growth of per capita income. Therefore, unless higher output exceeds population growth, we would expect a negative effect. For subnational entities, this relationship is unclear, because one part of population dynamics are migration patterns, which may vary across scale levels (Resende et al. 2016). We obtain population counts per municipality from the IBGE[4] and compute population growth again at five-year average rates.

In line with numerous other studies (e.g. Resende et al. 2016), we use population density as a proxy for agglomeration externalities. Population agglomeration effects have been considered in the economic geography literature. Denser populated (i.e. urban) regions are associated with positive effects on productivity growth, because they show higher rates of technological progress (Fingleton 2001). However, this relationship may not hold for poor districts in low and middle income countries, where strong urbanisation is caused by extensive population growth without having any substantial effects on labour productivity.

We furthermore follow LeSage and Fischer (2008) and include the gross value added (GVA) in the agriculture, industry and service sectors as control variables in order to proxy the industrial structure of municipalities.

Initial income, population growth and density, and the sectoral mix variables also enter

[3] We may consider the possibility of back-casting the data to 2002 in order to extend our panel.

[4] Population counts for 2007 and 2010 were interpolated due to missing data.

the forest loss regression. The empirical literature is inconclusive regarding the direction of the effect that income may have on forest cover (Busch and Ferretti-Gallon 2017), but, together with information on population growth and density and the industrial structure, these socioeconomic and demographic variables are included as control variables to to account for any other anthropogenic activity besides the mining and other land use change effects.

Final control variables for both models are the biophysical characteristics precipitation and elevation. The only variables included in the growth model, which are not used in the forest loss specification, are human capital and forest cover change accounts. While there is no obvious theoretical reasoning how human capital could influence forest cover, the problem with controlling for the latter is that changes from forest to any other land cover category effectively define forest loss, which is the dependent variable in this model.

Municipalities, the lowest administrative divisions in Brazil, are occasionally split or merged and hence the total number of municipalities varies. In order to keep a balanced panel with constant number of spatial observations and to ensure comparability, we follow a similar strategy as Resende et al. (2016) and only consider municipalities with unchanged geographical extent over the sample period. Ensuring constant geographical distances between observations strongly facilitates introducing spatial structure in the panel model, because neighbour-links (we use a k-nearest neighbours specification) remain the same for each year in the panel.

5 Results and discussion

We present MCMC estimation results for two models, one on regional economic growth rates and the other on forest loss patterns. 20,000 posterior draws were collected for each model, discarding the respective first 10,000 as burn-ins.[5] Further empirical settings were a k-nearest neighbours spatial weights specification with $k = 5$[6] and standard sampling procedures for the parameters β, θ and ρ as discussed in the Bayesian spatial econometric literature (LeSage and Pace 2009). Direct and indirect impact estimates for the growth model are shown in Table 2 and the forest loss model results are summarised in Table 3. Note that we excluded the time-specific intercepts for more concise summary tables.

5.1 The effects of mining on GDP

The top two lines of Table 2 reveal that local economic effects of mining activities are ambivalent for Brazil, because extent and direction of direct and indirect impacts alter significantly between two time segments.[7] We find that previous to 2010, mining municipalities on average exhibit 3.8% higher growth rates due to direct effects, with additional significant economic stimulus caused by economic spillovers (4.6%). These impact estimates of mining activities previous to 2010 are highly statistically significant and in strong contrast to the negative relationship that is typically found in cross-country comparisons (Sachs and Warner 2001). After 2010, however, the significant and positive direct effect disappears, i.e. there

[5]The diagnostics by Geweke (1992) were used to confirm convergence of the sampler.

[6]Results are robust against alternative neighbourhood definitions, see Appendix C.2.

[7]See Appendix B for a more nuanced exploration how impact estimates vary across sample periods.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Mining × pre 2010	3.344	**3.797**	4.235	3.585	**4.660**	5.746
Mining × since 2010	-0.795	-0.321	0.183	-2.946	**-1.816**	-0.730
$LUC^{Agriculture,Forest\ Plantation}$	-0.034	0.005	0.043	-0.131	-0.046	0.040
$LUC^{Agriculture,Grassland}$	-0.081	-0.038	0.003	-0.277	**-0.163**	-0.049
$LUC^{Agriculture,Pasture}$	-0.010	0.024	0.057	0.058	**0.130**	0.197
$LUC^{Natural\ Forest,Agriculture}$	0.008	**0.038**	0.066	-0.173	**-0.115**	-0.055
$LUC^{Natural\ Forest,Forest\ Plantation}$	0.013	**0.051**	0.087	0.142	**0.216**	0.288
$LUC^{Natural\ Forest,Grassland}$	-0.016	0.019	0.052	-0.126	**-0.062**	-0.002
$LUC^{Natural\ Forest,Pasture}$	0.001	**0.031**	0.062	-0.207	**-0.159**	-0.108
$LUC^{Forest\ Plantation,Agriculture}$	-0.016	0.021	0.061	0.026	**0.116**	0.215
$LUC^{Forest\ Plantation,Grassland}$	-0.012	0.059	0.133	-0.234	-0.033	0.164
$LUC^{Forest\ Plantation,Pasture}$	-0.054	-0.013	0.026	0.019	**0.130**	0.244
$LUC^{Grassland,Agriculture}$	0.081	**0.120**	0.161	0.002	**0.105**	0.207
$LUC^{Grassland,Forest\ Plantation}$	-0.041	0.016	0.074	-0.500	**-0.338**	-0.187
$LUC^{Grassland,Pasture}$	-0.082	-0.034	0.018	0.077	**0.190**	0.303
$LUC^{Pasture,Agriculture}$	0.038	**0.070**	0.102	-0.129	**-0.071**	-0.015
$LUC^{Pasture,Forest\ Plantation}$	-0.033	-0.001	0.033	-0.146	**-0.074**	-0.006
$LUC^{Pasture,Grassland}$	-0.029	0.023	0.067	-0.043	0.068	0.182
Initial Agriculture	1.380	**2.122**	2.925	-0.840	0.193	1.307
Initial Natural Forest	-1.624	**-0.887**	-0.209	1.482	**2.584**	3.569
Initial Forest Plantation	-2.964	-1.177	0.656	-12.846	**-9.217**	-5.596
Initial Grassland	-3.404	**-2.308**	-1.195	1.468	**3.269**	5.132
Initial Pasture	-1.311	-0.604	0.097	-0.194	0.829	1.798
Initial income	-3.717	**-3.589**	-3.466	2.013	**2.284**	2.547
Human capital	2.487	**3.203**	3.878	-3.083	**-2.138**	-1.102
Population growth	-0.422	**-0.396**	-0.371	-0.109	-0.045	0.025
Population density	-0.612	**-0.480**	-0.354	0.333	**0.550**	0.777
GVA agriculture	-0.205	**-0.138**	-0.075	-0.066	0.052	0.169
GVA industry	-0.465	**-0.400**	-0.337	-0.790	**-0.641**	-0.485
GVA services	0.688	**0.762**	0.838	0.291	**0.483**	0.654
Precipitation	-0.033	0.206	0.435	-0.068	0.173	0.414
Elevation	-0.001	-0.001	0.000	0.000	0.000	0.001
ρ	0.284	**0.293**	0.303			
Observations	47,241					

Table 2: Average direct and indirect impact estimates growth model. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual per capita growth rates. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

is no difference between mining and non-mining municipalities with respect to the direct presence of a mine. On the contrary, indirect effects now show a negative direction. The impact estimate of -1.8% can be read as such: The GDP of municipalities, which have mines present in their neighbouring municipalities, on average grew at almost 2% lower rates than those without mines in their surroundings.

One fundamental question is now why the positive direct and indirect economic stimulus from mines disappears over time. We turn our attention to the observation made earlier in Figure 1. There is a strong dependence between the Brazilian economy and global commodity prices. We believe that the Brazilian economic stagnation and crisis had a distinct influence, causing a turnaround in the relationship between mining and regional economies. Before 2010, a beneficial global environment (high prices and demand for materials) translated into direct regional economic growth, i.e. the revenues from mining as well as generated multiplier effects (e.g. via employment creation and accelerating demand for local goods and services) remained local to a notable extent. The presence of positive spillovers suggests the existence of diffused backward linkages such as via commuting workers and the emergence of mining clusters, i.e. the generation of endogenous development and diversification of the industrial mix due to agglomeration effects (Arias et al. 2013).

However, a growing extractive sector also interferes with other, potentially more sustainable, local economic structures such as small-scale agriculture or manufacturing and creates dependence on the mining industry (Aragón et al. 2015). When the commodity price bubble bursts and the subsequent economic crisis kicks in, this negative circle, again via backward linkages, also effects the neighbours of mining municipalities. In fact, our results suggest that it hits them even more severe than the mining municipalities themselves. This could be explained by reduced, but not entirely shut mining activities and the halt of expansion and investment in reaction to lowered profit expectations associated with decreasing commodity prices, where the involvement of actors from the surroundings (indirect effects) was reduced more substantially than for local actors (direct effects). This mechanism would explain the negative indirect impacts as compared to "only" insignificant direct effects in the period later than 2010.[8]

5.2 The effects of land use change on GDP

The second focus of the growth model lies on land use change effects, i.e. how transformations from one land cover category to another relate to the economic growth rates of municipalities. Table 2 summarises the related results, which are indicated by the LUC variables. A first view on direct effects suggests that economic growth is predominately induced by the transformation of land for agricultural use. These effects are strongest for changes from grassland to agriculture, where the estimate of 0.12 implies that a 5-year average increase by 10% in land use change of that specific transformation within one municipality on average leads to 1.2% higher GDP growth rates in this municipality. Further significant direct impacts are found for transformations from pasture to agriculture (0.07), natural forest to agriculture (0.04) and for natural forest to forest plantation (0.05) and to pasture (0.03). On the one hand, these results underline the productive potential of land transformation. On the other hand, they refer to potentially severe interference with natural systems. The most obvious problematic with land use change in Brazil are deforestation dynamics in the Amazon and along its borders (e.g. Soterroni et al. 2018). It is therefore an interesting finding that land use change referring to direct deforestation (transformation from natural forest to any other category) is associated with the smallest economic growth effects. Recent studies, however, also demonstrate pathways of land-conversion, suggesting that deforested land is commonly re-transformed, such as from natural forest first to pasture, and then to agriculture (Kuschnig et al. 2021). Full economic exploitation of land is therefore likely to develop a few years after clearing.

[8]This narrative requires further testing. Ideas are to ask specialists how/if mining was reduced after 2010, look for commuting data, and show that the effect can not come from the construction of our mining data. Another idea, motivated by the fact that fewer mines were opened after 2010, is to test if GDP-effects from mine openings are only short-term and vanish over time. This may be achieved with some kind of initial effects model taking first differences.

More detail and complexity is added to the relationship between land use change and GDP growth of Brazilian municipalities with spillover effects being additionally taken into account. While we find significant positive spillovers for transformations from grassland (0.19) and from agriculture to pasture (0.13), from grassland to agriculture (0.11), from natural forest to forest plantation (0.22), and from forest plantation to pasture (0.13) and to agriculture (0.12), the results suggest that there are also negative spillover effects on economic growth from land use change. This is most notably the case for land use change from grassland to forest plantation, where the effect is strongest among all land use change impact estimates (-0.34). Further negative spillovers are found for land use change from natural forest to pasture (-0.16), to agriculture (-0.12) and to grassland (-0.06), from agriculture to grassland (-0.16), as well as from pasture to agriculture (-0.07) and to forest plantation (-0.07). One possible explanation for negative impacts are environmental externalities, which may especially be the case for the establishment of large-scale forest plantation on former grassland as well as for land use change involving deforestation.

In addition to land use change effects, we can also interpret the effects of initial land cover classifications, i.e. the characteristicts of municipalities at the beginning of a 5-year growth window. The results suggest that one productive characteristic without any significant spillover is agriculture. The GDP of municipalities with 1% higher shares of agricultural land on average grows at approximately 2% higher rates. It is somewhat intuitive that municipalities with higher shares of land that is less frequently exploited for economic reasons (natural forest and grassland), on average show lower economic growth rates of approximately 1% and 2%, respectively. On top of that, findings reveal that the presence of grassland and natural forest has positive economic spillover effects, which even exceed the negative direct effects. Lastly, the results suggest that forest plantations, when established, do not have any direct GDP-effects. They do, however, exhibit strong negative indirect effects. This finding adds a new facet to the still limited and rather inconclusive literature on the socioeconomic effects of forest plantations. In a recent study, Afonso and Miller (2021) point towards numerous factors shaping the impacts of forest plantations, which are similar to what we have mentioned in the context of enclave and agglomeration effects of extraction projects. While the positive growth impact, which we found for land conversion to forest plantation, is in line with their story, these negative spillover effects (which they do not account for in their study) widen the narrative. Potential causes are environmental and social constraints placed on surroundings or migration flows, yet we must leave a definite answer to this question up to future research.

The impact estimates of the growth model are completed by a number of control variables, which are briefly summarised as follows: We find significant signs for the presence of growth convergence, which is indicated by the strong negative direct impact estimate for initial income, which exceeds counterbalancing positive spillover effects from high-income neighbours. This finding is in line with the theoretical and empirical growth literature (e.g. López-Bazo et al. 2004; Resende et al. 2016). For human capital, direct and indirect effects are in opposite direction, again conforming to earlier works (e.g. LeSage and Fischer 2008; Resende et al. 2016). As both, initial income and human capital, behave exactly as we would have expected from stylised facts about economic growth, we can be confident about our model. For population growth and population density, we find negative direct impacts, as well as no significant spillover for population growth and a positive indirect effect for population density.

Regarding the sectoral structure, strongest positive (direct and indirect) links are found for initial GVA in the service sector, while municipalities with large shares in the agriculture and industry sectors tend to grow at lower rates. Lastly, we turn the attention to ρ, the spatial parameter, which is clearly above zero, confirming the presence of significant spatial dependence.

5.3 The relationship between mining and forest loss

While the results above focused on the economic notion of resource-led development, we now turn the spotlight on another component of development and well-being in a broader sense: the environmental dimension of economic activities. Table 3 summarises estimation results for the forest loss model, which we set up in order to measure the environmental impacts of mining activities and other types of land use change.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	375.295	**594.358**	808.390	1561.998	**2397.302**	3205.026
Mining × since 2010	23.263	**248.423**	464.819	-829.280	36.482	906.420
$LUC^{Agriculture,Grassland}$	-19.504	0.961	21.439	-97.076	-6.372	73.074
$LUC^{Agriculture,Pasture}$	-4.470	9.843	24.588	-61.609	-10.710	35.944
$LUC^{Grassland,Agriculture}$	22.287	**41.615**	60.285	57.276	**138.343**	217.093
$LUC^{Grassland,Pasture}$	21.088	**43.714**	66.046	-110.962	-30.161	48.924
$LUC^{Pasture,Agriculture}$	3.567	**17.415**	30.875	-53.577	-16.032	26.303
$LUC^{Pasture,Grassland}$	53.556	**76.448**	99.143	40.131	**122.304**	205.747
Initial Agriculture	-614.002	-275.498	54.505	54.994	**751.474**	1437.908
Initial Natural Forest	355.430	**640.544**	940.362	645.686	**1242.076**	1848.759
Initial Forest Plantation	-1098.837	-349.339	453.652	-3264.232	-1302.316	873.717
Initial Grassland	-2132.823	**-1658.746**	-1193.426	-1677.020	-419.889	749.999
Initial Pasture	-833.443	**-544.768**	-261.732	971.710	**1582.022**	2142.313
Initial income	-120.647	**-61.978**	-6.566	-227.868	-61.735	92.026
Population growth	48.980	**61.291**	72.810	135.333	**183.971**	230.589
Population density	44.203	**95.757**	149.132	68.848	**238.320**	398.486
GVA agriculture	132.733	**162.171**	191.109	111.423	**194.334**	273.916
GVA industry	-17.364	12.274	41.388	-26.890	93.320	221.408
GVA services	-101.340	**-67.393**	-32.065	-325.510	**-180.219**	-34.660
Precipitation	3.259	**110.306**	218.326	-72.054	53.745	178.319
Elevation	-0.566	**-0.314**	-0.036	-0.117	0.258	0.594
ρ	0.612	**0.619**	0.622			
Observations	47,241					

Table 3: Average direct and indirect impact estimates forest loss model. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in ha. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

Impact estimates reveal that extractive activities are clearly associated with higher forest loss rates. The impact estimates for mining previous to 2010 suggest a direct impact of mines on forest loss of approximately 594 hectares per year and an even substantially higher indirect effect of almost 2,400 hectares. In contrast to the growth model, we do not see an entirely different picture for the years 2010-2013. The effects are, however, weaker. Direct effects are approximately half as strong as in the earlier period, and indirect effects turn insignificant for the more recent years.

Land use change variables indicate that land conversions from grassland and pasture have direct forest loss effects, and additional indirect effects are found for land use change from pasture to grassland and from grassland to agriculture. Changes from agricultural land back to grassland or pasture do not affect forest cover.

The land cover variables in the model are mostly in line with our expectations. High shares of initial natural forest cover have greater potential for forest loss, while municipalities that are initially dominated by grassland and pasture exhibit significantly lower forest loss. Spillover effects, however, are positive for all land cover classification except for forest plantation and grassland. Cleared land for agriculture or pasture is likely to induce more deforestation in neighbouring municipalities due to spatial links such as via infrastructure build up or other clustering effects. Already easily accessible and cleared areas make it easier to expand economic activities to their closest neighbours.

Drawing our attention to the remaining control variables, results further reveal that population growth and density are directly and indirectly positively related to forest loss, while negative direct effects can be found for initial income. The biophysical variables precipitation and elevation play a greater role in the forest loss model than in the growth model. High precipitation levels are positively related to forest loss, while municipalities at higher altitudes show lower forest loss rates. Neither of them, however, has any spillover effects. Lastly, note that forest loss exhibits strong spatial dependence ($\rho = 0.62$), supporting the need for spatial regression approaches.

5.4 Synthesis: fading trade-off effects

A combined view on the results of both models allows a more nuanced evaluation of the narrative of resource-led development at the cost of the environment (Hope 2019). In the early 21st century, when the mining industry boomed due to favourable global economic conditions, average incomes increased locally where and close to where the actual mining was taking place in Brazil. In terms of an economic perspective, yet still leaving aside any distributional aspects, this is in line with what the mining industry has argued for a long time, stressing the effects of employment creation, local procurement and other spatial externalities. For the same time period, however, we see a very clear link between mining activities and environmental destruction. In the same, economically successful, 5-year period between 2005 and 2009, we find strong evidence that extractive activities caused high rates of forest loss not even within, but also in the surroundings of mining municipalities. Together, the results suggest a trade-off between positive economic effects and negative environmental consequences, both via direct and indirect channels.

This trade-off is less clear for the years since 2010, when global economic conditions got less favourable for resource-dependent development strategies. On the one hand, there is no signal anymore for a positive link between mining and regional economic growth rates. The results rather suggest lower growth rates around mining regions due to indirect channels. On the other hand, our findings still suggest a negative relationship between mining and natural forest cover. Interestingly, this link is more locally concentrated in the period after 2010. Strong spatial diffusion of forest loss as found over the earlier period does not carry over to the more recent years. To summarise, this means that the situation changes from a trade-off characterised by high economic benefits and high environmental consequences to a scenario where economic benefits vanish and negative environmental consequences remain, but at less substantial magnitude.

It is not within the scope of this paper to bring forward any normative reasoning if and under which conditions such a trade-off between economic and environmental interests can be tolerated. What we can reason from the mere results of the two models employed in this study, however, is that such a trade-off can not be taken for granted. For the case of Brazil, our findings suggest no expansion of extractive activities in the name of regional development, as we do not find clear empirical evidence for a sustained existence of such as relationship, while environmental (and also social) consequences of such practice may be irreversible.

6 Conclusion

In this study, we connected resource-dependent economic development strategies and the environmental implications thereof with the empirical regional economic growth literature. The main research objectives were to identify and quantify the direct and indirect regional economic effects of mining and of other types of land use change, and to inform about potential trade-offs between economic and environmental effects. This was achieved employing two panel-structure spatial Durbin models, one each for modelling economic growth rates and forest loss area at the level of Brazilian municipalities. We considered annual data for the years 2005-2013 and allowed for a structural break of the effects of mining in 2010.

We found that the link between mining activities and the economic growth of municipalities is ambiguous, depending on the time span observed. Between 2005 and 2009, metals and minerals extraction was associated with higher GDP growth in mining municipalities and, due to spillover effects, their surroundings. When considering 2010-2013, direct impact estimates turned insignificant and spillover effects revealed a negative impact. Therefore, mining can not straightforwardly be argued to foster regional economic development, as this apparently depends on wider circumstances.

With regard to environmental impacts, our results suggest that mining is associated with higher rates of forest loss. This applies for both segments before and after 2010, but the effects are stronger in the earlier period, for which we moreover find substantial spillover effects that are absent later on. We hence conclude that there was a trade-off between economic and environmental effects, which faded in more recent years, when positive economic effects completely vanished, but mining-induced forest loss remained.

References

Afonso, Roberta and Daniel C Miller (2021). “Forest plantations and local economic development: Evidence from Minas Gerais, Brazil”. In: *Forest Policy and Economics* 133, p. 102618. DOI: 10.1016/j.forpol.2021.102618.

Alvarez-Berríos, Nora L and T Mitchell Aide (2015). “Global demand for gold is another threat for tropical forests”. In: *Environmental Research Letters* 10.1, p. 014006. DOI: 10.1088/1748-9326/10/1/014006.

Aragón, Fernando M, Punam Chuhan-Pole, and Bryan Christopher Land (2015). "The local economic impacts of resource abundance: What have we learned?" In: *World Bank Policy Research Working Paper No. 7263*. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2609380.

Aragón, Fernando M and Juan Pablo Rud (2013). "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine". In: *American Economic Journal: Economic Policy* 5.2, pp. 1–25. DOI: 10.1257/pol.5.2.1.

Arias, Martín, Miguel Atienza, and Jan Cademartori (2013). "Large mining enterprises and regional development in Chile: between the enclave and cluster". In: *Journal of Economic Geography* 14.1, pp. 73–95. DOI: 10.1093/jeg/lbt007.

Auty, Richard M (1993). *Sustaining development in mineral economies: The resource curse thesis.* New York: Routledge.

— (1995). "Industrial Policy, Sectoral Maturation, and Postwar Economic Growth in Brazil: The Resource Curse Thesis". In: *Economic Geography* 71.3, pp. 257–272. DOI: 10.2307/144311.

Azzoni, Carlos R (2001). "Economic growth and regional income inequality in Brazil". In: *The Annals of Regional Science* 35.1, pp. 133–152. DOI: 10.1007/s001680000038.

Baltagi, Badi H and Alain Pirotte (2010). "Panel data inference under spatial dependence". In: *Economic Modelling* 27.6, pp. 1368–1381. DOI: 10.1016/j.econmod.2010.07.004.

Barro, Robert J (1991). "Economic growth in a cross section of countries". In: *The Quarterly Journal of Economics* 106.2, pp. 407–443.

Busch, Jonah and Kalifi Ferretti-Gallon (2017). "What Drives Deforestation and What Stops It? A Meta-Analysis". In: *Review of Environmental Economics and Policy* 11.1, pp. 3–23. DOI: 10.1093/reep/rew013.

CRU (2021). *Climatic Research Unit (CRU) Time-Series (TS) Version 3.21 of High Resolution Gridded Data of Month-by-month Variation in Climate.* http://dx.doi.org/10.5285/D0E1585D-3417-485F-87AE-4FCECF10A992.

Caselli, Francesco, Gerardo Esquivel, and Fernando Lefort (1996). "Reopening the convergence debate: a new look at cross-country growth empirics". In: *Journal of economic growth* 1.3, pp. 363–389.

Cravo, Túlio Antonio and Guilherme Mendes Resende (2013). "Economic growth in Brazil: a spatial filtering approach". In: *The Annals of Regional Science* 50.2, pp. 555–575. DOI: 10.1007/s00168-012-0504-6.

Crespo Cuaresma, Jesus, Gernot Doppelhofer, and Martin Feldkircher (2014). "The Determinants of Economic Growth in European Regions". In: *Regional Studies* 48.1, pp. 44–67. DOI: 10.1080/00343404.2012.678824.

Cruz, Thiago Leite et al. (2020). "Measuring the social license to operate of the mining industry in an Amazonian town: A case study of Canaã dos Carajás, Brazil". In: *Resources Policy*, p. 101892. DOI: 10.1016/j.resourpol.2020.101892.

Elhorst, J Paul (2010). "Spatial Panel Data Models". In: *Handbook of applied spatial analysis.* Ed. by Getis Arthur Fischer Manfred M. Berlin, Heidelberg: Springer, 377–407.

Ertur, Cem and Wilfried Koch (2007). "Growth, technological interdependence and spatial externalities: theory and evidence". In: *Journal of Applied Econometrics* 22.6, pp. 1033–1062. DOI: 10.1002/jae.963.

Escobar, Herton (2020). "Deforestation in the Brazilian Amazon is still rising sharply". In: *Science* 369.6504, pp. 613–613. DOI: 10.1126/science.369.6504.613.

FIRJAN (2018). *Education index (IFDM Educação) Version 2018.* https://www.firjan.com.br/ifdm/downloads/.

Fingleton, Bernard (2001). “Theoretical economic geography and spatial econometrics: dynamic perspectives”. In: *Journal of Economic Geography* 1.2, pp. 201–225. DOI: 10.1093/jeg/1.2.201.
Geweke, John (1992). “Evaluating the accuracy of sampling-based approaches to the calculations of posterior moments”. In: *Bayesian Statistics*. Ed. by JM Bernardo et al. Vol. 4. Oxford: Oxford Univ., pp. 167–193.
Heilmayr, Robert et al. (2020). “Brazil’s Amazon soy moratorium reduced deforestation”. In: *Nature Food* 1.12, pp. 801–810. DOI: 10.1038/s43016-020-00194-5.
Hope, Mat (2019). “The Brazilian development agenda driving Amazon devastation”. In: *The Lancet Planetary Health* 3.10, e409–e411. DOI: 10.1016/S2542-5196(19)30195-0.
Humphreys, Macartan, Jeffrey D Sachs, and Joseph E Stiglitz, eds. (2007). *Escaping the resource curse*. New York: Columbia Univ.
IBGE (2021). *Instituto Brasileiro de Geografia e Estatística*. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística.
Keller, Wolfgang (2002). “Geographic Localization of International Technology Diffusion”. In: *American Economic Review* 92.1, pp. 120–142. DOI: 10.1257/000282802760015630.
Kuschnig, Nikolas et al. (2021). “Spatial spillover effects from agriculture drive deforestation in Mato Grosso, Brazil”. In: *Scientific Reports* 11, p. 21804. DOI: 10.1038/s41598-021-00861-y.
LeSage, James P and Manfred M Fischer (2008). “Spatial growth regressions: Model specification, estimation and interpretation”. In: *Spatial Economic Analysis* 3.3, pp. 275–304. DOI: 10.1080/17421770802353758.
LeSage, James P and Robert K Pace (2009). *Introduction to spatial econometrics*. Boca Raton: Taylor & Francis.
Lucas, Robert E (1988). “On the mechanics of economic development”. In: *Journal of Monetary Economics* 22.1, pp. 3–42. DOI: 10.1016/0304-3932(88)90168-7.
López-Bazo, Enrique, Esther Vayá, and Manuel Artís (2004). “Regional Externalities And Growth: Evidence From European Regions”. In: *Journal of Regional Science* 44.1, pp. 43–73. DOI: 10.1111/j.1085-9489.2004.00327.x.
MODIS (2021). *MODIS Vegetation Index Products (NDVI and EVI)*. https://modis.gsfc.nasa.gov/data/dataprod/mod13.php.
Machado, Iran F and Silvia F de M. Figueirôa (2001). “500 years of mining in Brazil: a brief review”. In: *Resources Policy* 27.1, pp. 9–24. DOI: 10.1016/S0301-4207(01)00004-6.
Mankiw, N Gregory, David Romer, and David N Weil (1992). “A contribution to the empirics of economic growth”. In: *The Quarterly Journal of Economics* 107.2, pp. 407–437.
Manzano, Osmel and Juan David Gutiérrez (2019). “The subnational resource curse: Theory and evidence”. In: *The Extractive Industries and Society* 6.2, pp. 261–266. DOI: 10.1016/j.exis.2019.03.010.
MapBiomas (2021). *Project MapBiomas – Collection 5.0 of Brazilian Land Cover Use Map Series*. https://mapbiomas.org/en/statistics.
Matlaba, Valente José et al. (2019). “Socioeconomic dynamics of a mining town in Amazon: a case study from Canaã dos Carajás, Brazil”. In: *Mineral Economics* 32.1, pp. 75–90. DOI: 10.1007/s13563-018-0159-6.
Maus, Victor et al. (2020). “A global-scale data set of mining areas”. In: *Scientific Data* 7.289. DOI: 10.1038/s41597-020-00624-w.
Paelinck, Jean and Leo Klaassen (1979). *Spatial econometrics*. Farnborough: Saxon House.
Resende, Guilherme Mendes (2011). “Multiple dimensions of regional economic growth: The Brazilian case, 19912000”. In: *Papers in Regional Science* 90.3, pp. 629–662. DOI: 10.1111/j.1435-5957.2010.00336.x.

Resende, Guilherme Mendes (2013). "Spatial dimensions of economic growth in Brazil". In: *International Scholarly Research Notices* 2013. DOI: 10.1155/2013/398021.

Resende, Guilherme Mendes et al. (2016). "Evaluating multiple spatial dimensions of economic growth in Brazil using spatial panel data models". In: *The Annals of Regional Science* 56.1, pp. 1–31. DOI: 10.1007/s00168-015-0706-9.

Romer, Paul M (1990). "Endogenous Technological Change". In: *Journal of Political Economy* 98.5, Part 2, S71–S102. DOI: 10.1086/261725.

Rorato, Ana Claudia et al. (2020). "Brazilian Amazon indigenous peoples threatened by mining bill". In: *Environmental Research Letters* in press. DOI: 10.1088/1748-9326/abb428.

SNL (2021). *Metals and Mining Database*. New York: S&P Global Market Intelligence.

Sachs, Jeffrey D and Andrew M Warner (1995). *Natural Resource Abundance and Economic Growth*. Working Paper 5398. National Bureau of Economic Research. DOI: 10.3386/w5398.

— (2001). "The curse of natural resources". In: *European Economic Review* 45.4, pp. 827–838. DOI: 10.1016/S0014-2921(01)00125-8.

Silva, Jordana Ferreira da et al. (2021). "Regional economic resilience and mining in the State of Minas Gerais/Brazil: The barriers of productive specialisation to formal employment and tax management". In: *Resources Policy* 70, p. 101937. DOI: 10.1016/j.resourpol.2020.101937.

Siqueira-Gay, Juliana et al. (2020). "Proposed Legislation to Mine Brazil's Indigenous Lands Will Threaten Amazon Forests and Their Valuable Ecosystem Services". In: *One Earth* 3.3, pp. 356–362. DOI: 10.1016/j.oneear.2020.08.008.

Solow, Robert M (1956). "A contribution to the theory of economic growth". In: *The Quarterly Journal of Economics* 70.1, pp. 65–94.

Sonter, Laura J et al. (2017). "Mining drives extensive deforestation in the Brazilian Amazon". In: *Nature Communications* 8.1, p. 1013. DOI: 10.1038/s41467-017-00557-w.

Soterroni, Aline C et al. (2018). "Future environmental and agricultural impacts of Brazil's Forest Code". In: *Environmental Research Letters* 13.7, p. 074021. DOI: 10.1088/1748-9326/aaccbb.

USGS (2021). *Global Multi-resolution Terrain Elevation Data GMTED2010*. https://www.usgs.gov/core-science-systems/eros/coastal-changes-and-impacts/gmted2010.

World Bank (2021a). *Commodity markets*. https://www.worldbank.org/en/research/commodity-markets.

— (2021b). *World Development Indicators*. https://databank.worldbank.org/source/world-development-indicators.

Zeileis, Achim et al. (2002). "strucchange: An R Package for Testing for Structural Change in Linear Regression Models". In: *Journal of Statistical Software* 7.2, pp. 1–38. DOI: 10.18637/jss.v007.i02.

de Area Leão Pereira, Eder Johnson et al. (2019). "Policy in Brazil (2016–2019) threaten conservation of the Amazon rainforest". In: *Environmental Science Policy* 100, pp. 8–12. DOI: 10.1016/j.envsci.2019.06.001.

van der Hoff, Richard and Raoni Rajão (2020). "The politics of environmental market instruments: Coalition building and knowledge filtering in the regulation of forest certificates trading in Brazil". In: *Land Use Policy* 96, p. 104666. DOI: 10.1016/j.landusepol.2020.104666.

Appendix

A Identification of mine openings

Searching structural breaks algorithm:

1. Use 2000-2020 250 m resolution time series (16-day intervals) from MODIS (2021) and compute average NDVI per mining polygon for all 459 polygons contained in the data set by Maus et al. (2020).

2. Identify segments according to structural breaks in NDVI time series using the 'strucchange' package in R (Zeileis et al. 2002).

3. Compute NDVI mean for each segment.

4. Set opening date as the month of first negative NDVI shock where means of segments change by more than 0.1 (see Figure 3 for examples). As robustness checks, we also applied this rule using 0.05 and 0.15 thresholds, because negative shocks may be present at weaker steps than the set threshold (as demonstrated in Figure 4).

5. If no such structural break exists in the time-series, we assume the mine has opened already previous to 2000 (Figure 5).

See Figures 6 and 7 for differences in mine openings across Brazil using alternative 0.05 and 0.15 thresholds. As expected, a smaller threshold identifies more mine openings instead of setting the opening to 2000 due to a lack of a sufficiently large NDVI shock. Model comparisons in Appendix C.1 show that results are robust against variations in this identification procedure.

Note that the algorithm is not intended to detect any mine closures (which would be a very complex undertaking). We argue that as soon as mining takes place in a certain municipality, it is very unlikely that mining operations will completely disappear in the respective area, because (a) large scale mining operations are extremely costly and hence have a long exploitation horizon and (b) once economically profitable recovery of ore is exhausted, an expansion to new deposits is typically conducted not far from the original mining site.

A current limitation is that the identification of mine openings is still missing validation of the produced data. One next step is to create a validation data set using visual interpretation of satellite imagery time series.

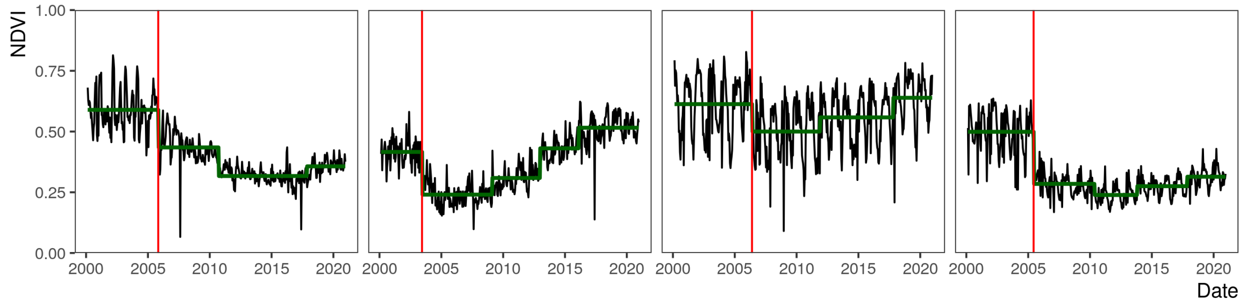


Figure 3: NDVI time series and identification of mine openings. Selected NDVI time series, segment means (green) and mine opening date detected by the algorithm (red) for a threshold of a drop in segment mean > 0.1. Polygon IDs: 2,146, 2,149, 3,467 and 3,941.

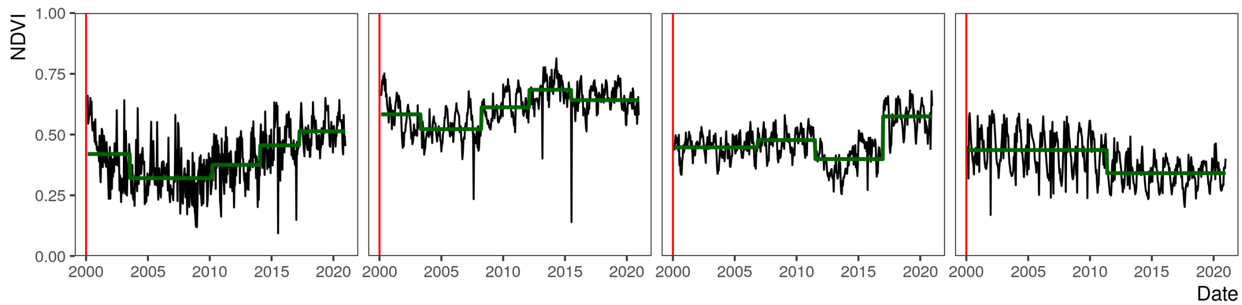


Figure 4: NDVI time series and missed identification of mine openings. Selected NDVI time series and segment means (green). No significant drop (> 0.1) in NDVI means was detected and hence opening date was set to the start of the time series (red). Polygon IDs: 2,180, 2,182, 2,266 and 3,377.

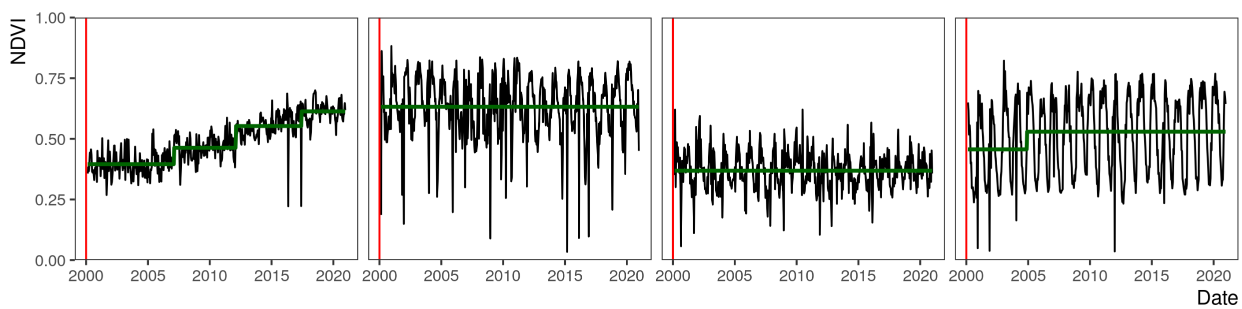


Figure 5: NDVI time series for polygons without vegetation decline. Selected NDVI time series and segment means (green). No decline in NDVI means detected and hence opening date was set to the start of the time series (red). Polygon IDs: 2,156, 3,491, 3,499 and 4,019.

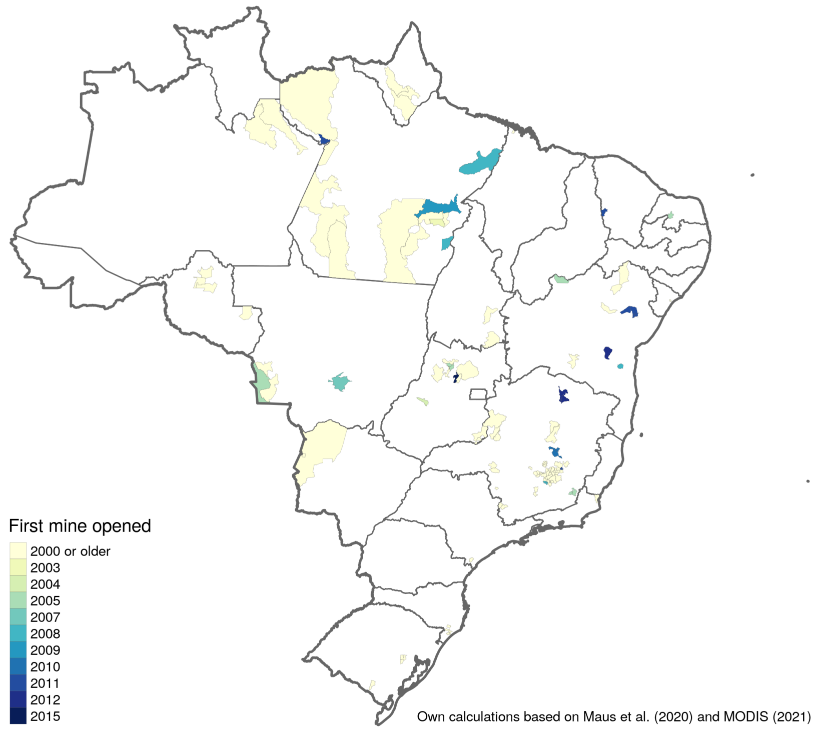
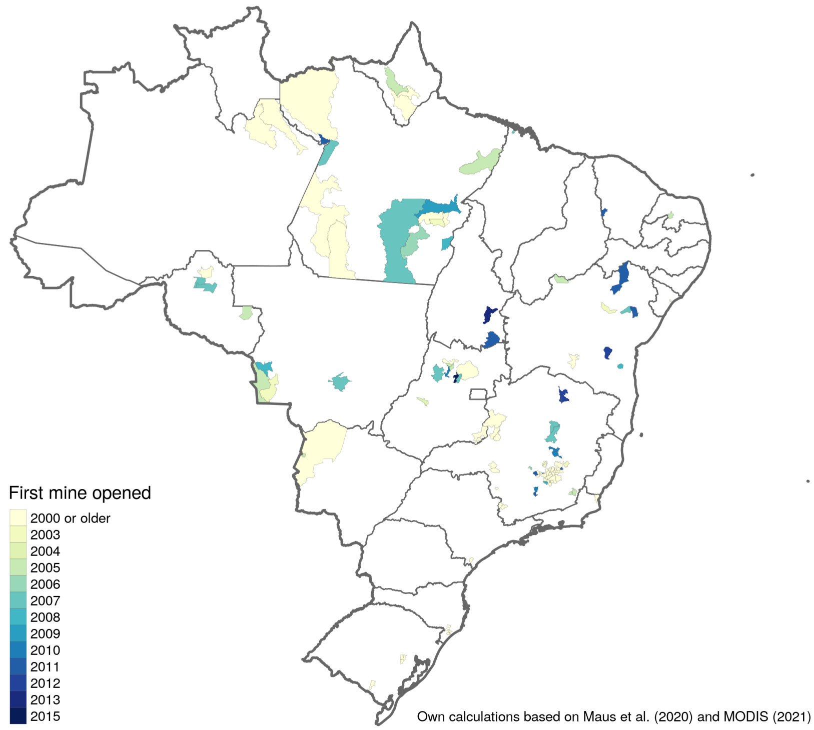
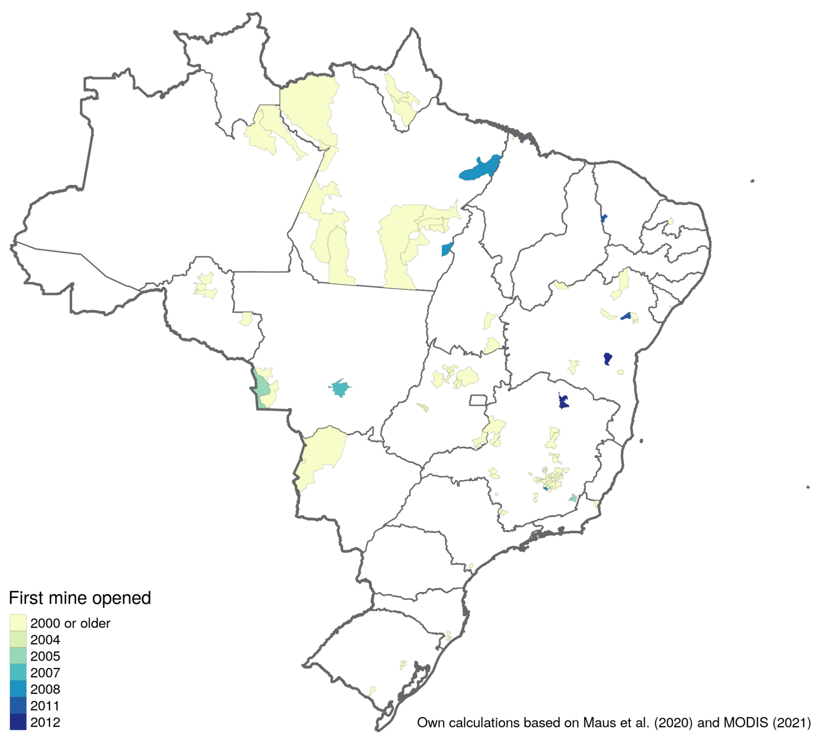


Figure 6: Identification of opening years for first mine in municipality. Threshold for minimum drop between NDVI segments is 0.1.



(a) Structural break threshold is 0.05



(b) Structural break threshold is 0.15

Figure 7: Alternative identification of opening years for first mine in municipality. Thresholds for minimum drop between NDVI segments are 0.05 and 0.15.

B Effect of mining on GDP across sample periods

Impact estimate of mining on GDP depends on the sample. Significantly positive effects change to insignificant direct and negative indirect effects when considering more recent years only:

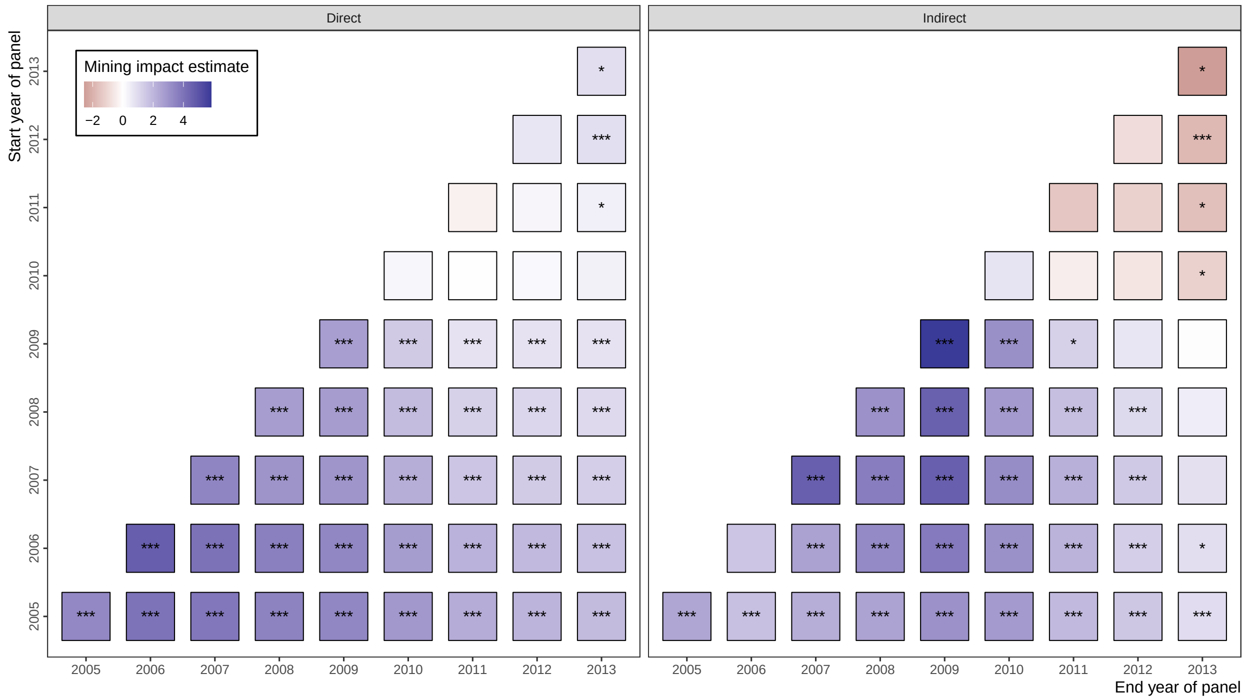


Figure 8: Mining impacts on GDP across sample periods. Average direct and indirect impact estimates of mining on GDP (panel SDM, considering time fixed effects); 2005-2013; dependent variable is 5-year average annual per capita growth rates. Three (one) stars indicate estimates statistically different from zero based on the 98 (90) percent posterior credible interval.

C Robustness

C.1 Alternative thresholds for mine opening identification

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	3.422	**3.831**	4.297	3.772	**4.643**	5.659
Mining × since 2010	-0.748	-0.335	0.133	-2.631	**-1.738**	-0.706
$LUC^{Agriculture,Forest\ Plantation}$	-0.034	0.005	0.047	-0.124	-0.048	0.040
$LUC^{Agriculture,Grassland}$	-0.079	-0.036	0.009	-0.254	**-0.160**	-0.052
$LUC^{Agriculture,Pasture}$	-0.011	0.022	0.048	0.065	**0.126**	0.193
$LUC^{Natural\ Forest,Agriculture}$	0.015	**0.040**	0.064	-0.164	**-0.113**	-0.050
$LUC^{Natural\ Forest,Forest\ Plantation}$	0.011	**0.049**	0.080	0.143	**0.201**	0.274
$LUC^{Natural\ Forest,Grassland}$	-0.009	0.018	0.051	-0.119	-0.056	0.007
$LUC^{Natural\ Forest,Pasture}$	0.001	**0.032**	0.061	-0.212	**-0.156**	-0.104
$LUC^{Forest\ Plantation,Agriculture}$	-0.010	0.021	0.064	0.013	**0.117**	0.197
$LUC^{Forest\ Plantation,Grassland}$	-0.025	0.053	0.136	-0.230	-0.032	0.192
$LUC^{Forest\ Plantation,Pasture}$	-0.050	-0.016	0.032	0.039	**0.130**	0.211
$LUC^{Grassland,Agriculture}$	0.075	**0.116**	0.162	-0.031	0.102	0.198
$LUC^{Grassland,Forest\ Plantation}$	-0.042	0.022	0.090	-0.464	**-0.320**	-0.186
$LUC^{Grassland,Pasture}$	-0.082	-0.032	0.007	0.051	**0.171**	0.278
$LUC^{Pasture,Agriculture}$	0.046	**0.071**	0.103	-0.125	**-0.070**	-0.022
$LUC^{Pasture,Forest\ Plantation}$	-0.029	0.001	0.035	-0.136	**-0.070**	-0.008
$LUC^{Pasture,Grassland}$	-0.027	0.022	0.070	-0.046	0.066	0.181
Initial Agriculture	1.273	**2.006**	2.734	-1.032	0.186	1.144
Initial Natural Forest	-1.648	**-1.015**	-0.457	1.738	**2.698**	3.714
Initial Forest Plantation	-3.055	-1.203	0.621	-12.325	**-8.855**	-5.743
Initial Grassland	-3.621	**-2.395**	-1.504	1.732	**3.420**	5.210
Initial Pasture	-1.343	**-0.774**	-0.160	0.102	**1.001**	1.898
Initial income	-3.703	**-3.586**	-3.475	2.155	**2.350**	2.579
Human capital	2.550	**3.211**	3.958	-3.049	**-2.236**	-1.418
Population growth	-0.418	**-0.394**	-0.368	-0.085	-0.024	0.033
Population density	-0.595	**-0.482**	-0.334	0.327	**0.547**	0.796
GVA agriculture	-0.196	**-0.132**	-0.055	-0.064	0.056	0.152
GVA industry	-0.441	**-0.390**	-0.331	-0.753	**-0.599**	-0.457
GVA services	0.672	**0.746**	0.811	0.268	**0.432**	0.597
Precipitation	-0.052	0.193	0.452	-0.089	0.173	0.397
Elevation	-0.001	-0.001	0.000	0.000	0.000	0.001
ρ	0.284	**0.295**	0.303			
Observations	47,241					

Table 4: Impact estimates growth model with alternative 0.05 NDVI threshold. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual per capita growth rates. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Mining × pre 2010	3.523	**3.952**	4.362	3.765	**4.659**	5.648
Mining × since 2010	-0.684	-0.237	0.186	-2.802	**-1.716**	-0.624
$\text{LUC}^{Agriculture,Forest\ Plantation}$	-0.034	0.007	0.039	-0.122	-0.040	0.047
$\text{LUC}^{Agriculture,Grassland}$	-0.080	-0.040	0.007	-0.276	**-0.155**	-0.049
$\text{LUC}^{Agriculture,Pasture}$	-0.003	0.027	0.061	0.053	**0.119**	0.187
$\text{LUC}^{Natural\ Forest,Agriculture}$	0.008	**0.041**	0.068	-0.164	**-0.113**	-0.056
$\text{LUC}^{Natural\ Forest,Forest\ Plantation}$	0.016	**0.049**	0.085	0.137	**0.214**	0.288
$\text{LUC}^{Natural\ Forest,Grassland}$	-0.019	0.014	0.042	-0.113	-0.057	0.005
$\text{LUC}^{Natural\ Forest,Pasture}$	-0.011	0.029	0.059	-0.203	**-0.158**	-0.104
$\text{LUC}^{Forest\ Plantation,Agriculture}$	-0.015	0.017	0.050	0.038	**0.117**	0.194
$\text{LUC}^{Forest\ Plantation,Grassland}$	-0.011	0.058	0.118	-0.293	-0.056	0.175
$\text{LUC}^{Forest\ Plantation,Pasture}$	-0.048	-0.016	0.025	0.036	**0.129**	0.261
$\text{LUC}^{Grassland,Agriculture}$	0.077	**0.124**	0.164	0.007	**0.100**	0.191
$\text{LUC}^{Grassland,Forest\ Plantation}$	-0.050	0.014	0.065	-0.481	**-0.334**	-0.204
$\text{LUC}^{Grassland,Pasture}$	-0.075	-0.032	0.012	0.092	**0.179**	0.271
$\text{LUC}^{Pasture,Agriculture}$	0.039	**0.069**	0.098	-0.128	**-0.065**	-0.012
$\text{LUC}^{Pasture,Forest\ Plantation}$	-0.028	0.001	0.033	-0.130	**-0.075**	-0.007
$\text{LUC}^{Pasture,Grassland}$	-0.015	0.023	0.072	-0.027	0.066	0.168
Initial Agriculture	1.250	**2.072**	2.891	-0.910	0.217	1.412
Initial Natural Forest	-1.628	**-0.922**	-0.092	1.603	**2.611**	3.622
Initial Forest Plantation	-2.958	-1.224	0.805	-12.762	**-9.262**	-5.676
Initial Grassland	-3.443	**-2.263**	-1.073	1.229	**3.061**	4.913
Initial Pasture	-1.257	-0.581	0.099	-0.233	0.809	1.664
Initial income	-3.716	**-3.604**	-3.475	2.093	**2.310**	2.518
Human capital	2.568	**3.277**	3.882	-3.078	**-2.155**	-1.212
Population growth	-0.421	**-0.396**	-0.371	-0.089	-0.038	0.019
Population density	-0.633	**-0.476**	-0.360	0.303	**0.555**	0.817
GVA agriculture	-0.192	**-0.128**	-0.051	-0.050	0.057	0.143
GVA industry	-0.447	**-0.396**	-0.348	-0.775	**-0.627**	-0.500
GVA services	0.693	**0.753**	0.816	0.306	**0.463**	0.653
Precipitation	-0.048	0.179	0.407	-0.103	0.187	0.434
Elevation	-0.001	-0.001	0.000	-0.001	0.000	0.001
ρ	0.284	**0.288**	0.294			
Observations	47,241					

Table 5: Impact estimates growth model with alternative 0.15 NDVI threshold. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual per capita growth rates. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	88.973	**330.662**	575.564	1077.437	**2016.259**	2712.107
Mining × since 2010	2.057	**221.712**	410.514	-664.180	82.133	915.205
$LUC^{Agriculture,Grassland}$	-15.121	1.402	22.199	-69.087	0.357	91.264
$LUC^{Agriculture,Pasture}$	-8.179	9.243	25.692	-58.821	-11.889	28.413
$LUC^{Grassland,Agriculture}$	19.956	**40.552**	56.637	50.158	**140.657**	205.592
$LUC^{Grassland,Pasture}$	24.586	**44.446**	62.778	-95.139	-34.886	64.780
$LUC^{Pasture,Agriculture}$	5.808	**18.339**	30.413	-41.714	-12.408	22.163
$LUC^{Pasture,Grassland}$	55.470	**77.690**	99.723	24.459	**126.384**	204.466
Initial Agriculture	-564.091	-249.616	62.253	144.965	**767.619**	1489.671
Initial Natural Forest	339.147	**674.120**	963.420	692.940	**1213.410**	1771.330
Initial Forest Plantation	-1102.675	-374.286	338.494	-3292.152	-1216.763	930.981
Initial Grassland	-2073.267	**-1626.303**	-1117.257	-1740.873	-427.798	684.739
Initial Pasture	-881.932	**-515.042**	-227.789	1000.179	**1584.790**	2057.671
Initial income	-106.458	**-58.670**	-13.053	-224.256	-67.176	57.561
Population growth	46.704	**61.837**	77.400	139.373	**179.716**	227.465
Population density	38.771	**99.278**	168.838	67.238	**236.535**	387.338
GVA agriculture	130.148	**159.075**	190.455	107.083	**179.707**	256.083
GVA industry	-13.654	15.130	43.968	-19.408	109.510	223.437
GVA services	-101.029	**-69.366**	-37.611	-348.425	**-194.517**	-28.278
Precipitation	7.878	**111.891**	190.357	-43.907	59.825	157.026
Elevation	-0.510	**-0.305**	-0.091	-0.054	0.260	0.570
ρ	0.612	**0.619**	0.632			
Observations	47,241					

Table 6: Impact estimates forest loss model with alternative 0.05 NDVI threshold. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in ha. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	544.351	**732.721**	919.270	1175.861	**1821.745**	2567.433
Mining × since 2010	53.680	**237.023**	446.835	-837.177	-128.536	756.305
$LUC^{Agriculture,Grassland}$	-17.953	0.439	18.179	-84.847	-0.309	73.663
$LUC^{Agriculture,Pasture}$	-7.402	8.945	24.036	-69.237	-9.459	36.807
$LUC^{Grassland,Agriculture}$	29.301	**43.187**	62.238	46.506	**133.404**	205.782
$LUC^{Grassland,Pasture}$	26.087	**45.946**	66.440	-104.834	-33.062	45.809
$LUC^{Pasture,Agriculture}$	3.405	**17.437**	32.368	-50.429	-13.010	28.768
$LUC^{Pasture,Grassland}$	53.575	**74.694**	99.545	37.334	**118.842**	187.980
Initial Agriculture	-535.783	-244.240	49.974	73.552	**677.876**	1389.734
Initial Natural Forest	401.011	**669.399**	887.898	626.013	**1126.807**	1682.642
Initial Forest Plantation	-927.249	-323.815	357.222	-3327.779	-1388.792	503.200
Initial Grassland	-2080.439	**-1648.620**	-1288.519	-1595.033	-491.048	625.380
Initial Pasture	-770.364	**-505.750**	-202.707	937.875	**1495.833**	2074.184
Initial income	-119.690	**-62.560**	-3.350	-210.828	-53.823	117.843
Population growth	49.478	**61.104**	72.200	127.558	**176.559**	223.625
Population density	51.359	**93.873**	142.603	65.746	**220.467**	388.388
GVA agriculture	138.410	**160.068**	184.258	104.450	**179.659**	254.526
GVA industry	-20.825	10.729	45.212	-36.633	93.767	207.937
GVA services	-99.010	**-64.408**	-27.775	-299.178	**-176.118**	-72.360
Precipitation	31.340	**119.783**	212.127	-60.708	36.751	151.514
Elevation	-0.570	**-0.319**	-0.033	-0.104	0.269	0.564
ρ	0.612	**0.619**	0.622			
Observations	47,241					

Table 7: Impact estimates forest loss model with alternative 0.15 NDVI threshold. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in ha. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

C.2 Alternative weights matrices

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Mining × pre 2010	3.027	**3.583**	4.024	4.935	**6.068**	7.265
Mining × since 2010	-0.629	-0.191	0.300	-3.861	**-2.695**	-1.436
$\text{LUC}^{Agriculture,Forest\ Plantation}$	-0.024	0.006	0.039	-0.204	-0.070	0.050
$\text{LUC}^{Agriculture,Grassland}$	-0.066	-0.027	0.010	-0.253	**-0.118**	-0.002
$\text{LUC}^{Agriculture,Pasture}$	-0.022	0.014	0.047	0.103	**0.169**	0.247
$\text{LUC}^{Natural\ Forest,Agriculture}$	0.015	**0.041**	0.066	-0.209	**-0.129**	-0.065
$\text{LUC}^{Natural\ Forest,Forest\ Plantation}$	0.024	**0.048**	0.077	0.164	**0.237**	0.324
$\text{LUC}^{Natural\ Forest,Grassland}$	-0.016	0.014	0.048	-0.130	-0.062	0.009
$\text{LUC}^{Natural\ Forest,Pasture}$	0.008	**0.036**	0.066	-0.232	**-0.179**	-0.135
$\text{LUC}^{Forest\ Plantation,Agriculture}$	-0.034	0.015	0.052	0.016	**0.136**	0.223
$\text{LUC}^{Forest\ Plantation,Grassland}$	-0.026	0.055	0.136	-0.231	-0.020	0.197
$\text{LUC}^{Forest\ Plantation,Pasture}$	-0.050	-0.011	0.039	0.001	**0.114**	0.223
$\text{LUC}^{Grassland,Agriculture}$	0.074	**0.122**	0.164	-0.064	0.047	0.178
$\text{LUC}^{Grassland,Forest\ Plantation}$	-0.036	0.021	0.083	-0.632	**-0.428**	-0.257
$\text{LUC}^{Grassland,Pasture}$	-0.100	-0.049	0.007	0.128	**0.242**	0.361
$\text{LUC}^{Pasture,Agriculture}$	0.047	**0.084**	0.113	-0.158	**-0.099**	-0.037
$\text{LUC}^{Pasture,Forest\ Plantation}$	-0.035	-0.003	0.033	-0.123	-0.057	0.018
$\text{LUC}^{Pasture,Grassland}$	-0.020	0.028	0.079	-0.065	0.056	0.175
Initial Agriculture	1.026	**1.690**	2.508	-0.235	0.755	1.934
Initial Natural Forest	-1.474	**-0.963**	-0.293	2.055	**2.866**	3.821
Initial Forest Plantation	-3.204	-1.565	0.179	-13.261	**-9.882**	-6.048
Initial Grassland	-3.544	**-2.318**	-1.253	1.269	**3.523**	6.050
Initial Pasture	-1.317	**-0.738**	-0.055	-0.033	1.021	2.089
Initial income	-3.733	**-3.640**	-3.505	2.158	**2.470**	2.706
Human capital	2.659	**3.267**	4.044	-3.787	**-2.705**	-1.632
Population growth	-0.408	**-0.389**	-0.366	-0.150	**-0.067**	-0.003
Population density	-0.509	**-0.405**	-0.292	0.186	**0.464**	0.728
GVA agriculture	-0.203	**-0.129**	-0.072	-0.061	0.037	0.155
GVA industry	-0.436	**-0.382**	-0.318	-0.831	**-0.659**	-0.466
GVA services	0.670	**0.749**	0.825	0.243	**0.473**	0.701
Precipitation	-0.048	0.222	0.495	-0.123	0.151	0.425
Elevation	-0.001	-0.001	0.000	0.000	0.000	0.001
ρ	0.333	**0.345**	0.353			
Observations	47,241					

Table 8: Impact estimates growth model with alternative k = 7 nearest neighbours W. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual per capita growth rates. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	3.160	**3.605**	4.048	5.525	**6.842**	8.190
Mining × since 2010	-0.830	-0.358	0.146	-2.816	**-1.877**	-0.806
$\text{LUC}^{Agriculture,Forest\ Plantation}$	-0.036	0.002	0.042	-0.157	-0.046	0.057
$\text{LUC}^{Agriculture,Grassland}$	-0.072	-0.032	0.005	-0.241	-0.094	0.041
$\text{LUC}^{Agriculture,Pasture}$	-0.024	0.008	0.043	0.094	**0.173**	0.255
$\text{LUC}^{Natural\ Forest,Agriculture}$	0.011	**0.041**	0.070	-0.203	**-0.133**	-0.051
$\text{LUC}^{Natural\ Forest,Forest\ Plantation}$	0.020	**0.050**	0.089	0.141	**0.214**	0.315
$\text{LUC}^{Natural\ Forest,Grassland}$	-0.011	0.018	0.047	-0.167	**-0.087**	-0.005
$\text{LUC}^{Natural\ Forest,Pasture}$	0.000	**0.029**	0.054	-0.232	**-0.174**	-0.126
$\text{LUC}^{Forest\ Plantation,Agriculture}$	-0.029	0.016	0.051	0.041	**0.162**	0.278
$\text{LUC}^{Forest\ Plantation,Grassland}$	-0.012	0.048	0.114	-0.392	-0.086	0.176
$\text{LUC}^{Forest\ Plantation,Pasture}$	-0.056	-0.014	0.021	-0.034	0.110	0.257
$\text{LUC}^{Grassland,Agriculture}$	0.086	**0.124**	0.161	-0.077	0.065	0.188
$\text{LUC}^{Grassland,Forest\ Plantation}$	-0.034	0.024	0.081	-0.599	**-0.408**	-0.222
$\text{LUC}^{Grassland,Pasture}$	-0.093	-0.043	0.005	0.078	**0.227**	0.362
$\text{LUC}^{Pasture,Agriculture}$	0.054	**0.088**	0.117	-0.168	**-0.108**	-0.051
$\text{LUC}^{Pasture,Forest\ Plantation}$	-0.041	-0.005	0.022	-0.118	-0.035	0.054
$\text{LUC}^{Pasture,Grassland}$	-0.022	0.022	0.072	-0.080	0.081	0.229
Initial Agriculture	0.383	**1.291**	2.065	-0.044	1.307	2.980
Initial Natural Forest	-1.697	**-0.895**	-0.278	1.582	**2.844**	4.133
Initial Forest Plantation	-3.579	**-1.641**	-0.031	-15.995	**-11.275**	-6.581
Initial Grassland	-3.210	**-2.363**	-1.369	0.896	**3.216**	5.967
Initial Pasture	-1.293	-0.713	0.008	-0.214	0.980	2.354
Initial income	-3.765	**-3.633**	-3.466	2.232	**2.477**	2.759
Human capital	2.766	**3.386**	4.103	-3.953	**-3.056**	-1.845
Population growth	-0.411	**-0.390**	-0.368	-0.115	-0.040	0.039
Population density	-0.506	**-0.371**	-0.238	0.107	**0.424**	0.751
GVA agriculture	-0.190	**-0.117**	-0.059	-0.132	0.024	0.167
GVA industry	-0.464	**-0.402**	-0.323	-0.765	**-0.549**	-0.403
GVA services	0.703	**0.767**	0.830	0.166	**0.340**	0.571
Precipitation	0.002	**0.261**	0.478	-0.138	0.110	0.365
Elevation	-0.002	-0.001	0.000	0.000	0.001	0.001
ρ	0.373	**0.379**	0.383			
Observations	47,241					

Table 9: Impact estimates growth model with alternative k = 9 nearest neighbours W. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual per capita growth rates. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Mining × pre 2010	451.615	**644.072**	859.076	2460.608	**3418.858**	4435.588
Mining × since 2010	-28.591	206.777	409.281	-442.244	505.300	1527.827
$LUC^{Agriculture,Grassland}$	-21.757	0.377	21.278	-83.142	31.730	139.480
$LUC^{Agriculture,Pasture}$	-7.179	6.471	20.658	-39.965	21.760	85.467
$LUC^{Grassland,Agriculture}$	18.484	**38.241**	57.544	34.689	**147.647**	233.573
$LUC^{Grassland,Pasture}$	22.099	**43.236**	64.944	-134.342	-27.737	53.888
$LUC^{Pasture,Agriculture}$	10.162	**20.680**	32.429	-104.892	**-56.824**	-8.495
$LUC^{Pasture,Grassland}$	55.959	**77.413**	96.326	-2.843	105.304	212.686
Initial Agriculture	-650.791	**-308.971**	-10.408	90.160	**1031.055**	1807.338
Initial Natural Forest	252.847	**539.024**	817.624	1039.015	**1745.085**	2459.352
Initial Forest Plantation	-1106.581	-394.084	336.894	-3688.405	-1362.732	914.229
Initial Grassland	-2101.430	**-1564.503**	-1208.213	-1988.657	-569.519	843.982
Initial Pasture	-927.097	**-622.068**	-350.624	1426.904	**2043.394**	2716.025
Initial income	-115.365	**-65.941**	-0.988	-267.052	-62.847	117.022
Population growth	48.610	**59.319**	68.308	167.759	**226.856**	284.602
Population density	53.565	**89.950**	130.462	114.901	**324.701**	516.353
GVA agriculture	136.334	**161.243**	184.087	149.485	**254.087**	369.106
GVA industry	-11.700	11.481	36.745	15.830	**172.616**	329.409
GVA services	-96.308	**-68.659**	-39.604	-486.021	**-283.919**	-104.970
Precipitation	12.675	**102.395**	195.927	-86.084	40.233	166.721
Elevation	-0.596	**-0.365**	-0.092	0.064	**0.416**	0.770
ρ	0.691	**0.695**	0.701			
Observations	47,241					

Table 10: Impact estimates forest loss model with alternative k = 7 nearest neighbours W. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in *ha*. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Mining × pre 2010	448.477	**660.915**	882.935	2911.746	**4125.045**	5140.814
Mining × since 2010	3.908	**222.406**	392.676	-314.804	866.545	2199.908
$\text{LUC}^{Agriculture,Grassland}$	-18.146	7.859	27.757	-135.565	20.332	157.289
$\text{LUC}^{Agriculture,Pasture}$	-8.301	7.814	19.861	-42.095	15.771	79.570
$\text{LUC}^{Grassland,Agriculture}$	12.264	**35.392**	53.516	-63.515	82.031	229.092
$\text{LUC}^{Grassland,Pasture}$	21.468	**39.906**	58.638	-168.003	-49.911	96.106
$\text{LUC}^{Pasture,Agriculture}$	9.423	**22.645**	36.797	-131.223	**-74.853**	-30.352
$\text{LUC}^{Pasture,Grassland}$	52.890	**77.060**	97.063	40.273	**193.746**	359.884
Initial Agriculture	-782.614	**-417.322**	-155.042	613.473	**1466.234**	2394.824
Initial Natural Forest	151.698	**453.706**	724.195	1268.219	**2019.307**	2957.165
Initial Forest Plantation	-1177.207	-446.761	360.010	-4840.617	-1813.822	1194.589
Initial Grassland	-2163.688	**-1687.999**	-1350.134	-1518.259	544.506	2265.990
Initial Pasture	-1018.934	**-710.335**	-457.777	1657.140	**2317.530**	3101.552
Initial income	-97.596	-52.438	6.815	-327.600	-155.023	70.394
Population growth	45.230	**56.667**	68.681	130.348	**219.097**	284.310
Population density	36.335	**84.370**	134.449	45.210	**292.897**	493.015
GVA agriculture	135.302	**163.730**	194.617	168.978	**261.448**	359.909
GVA industry	-18.562	10.183	42.659	94.446	**274.468**	454.336
GVA services	-103.206	**-68.712**	-25.166	-550.652	**-337.084**	-104.899
Precipitation	-12.523	84.114	195.508	-62.932	66.711	211.004
Elevation	-0.570	**-0.305**	-0.061	-0.129	0.300	0.664
ρ	0.721	**0.733**	0.741			
Observations	47,241					

Table 11: Impact estimates forest loss model with alternative k = 9 nearest neighbours W. Panel-structure (2005-2013) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in *ha*. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean.