Do Landslides Impact Urbanization Patterns? Evidence from Brazilian Cities

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Abstract

This paper investigates the impact of landslides on the subsequent urbanization patterns of Brazilian cities. Combining satellite data with detailed landslide records and adopting a staggered Difference-in-Differences approach, we show that municipalities exposed to landslides experience an average reduction of -6.45% to -8.71% in the size of their area that strongly persists over time. Additionally, these cities present a greater fragmentation of their built-up area. This evidence suggests that landslides are an important push-down force of urban agglomeration in Brazilian cities. We also show that this result can be partially explained by the sharp reduction in housing stock loans and the slowing down of economic activity that follows the landslide events.

Keywords: Landslides, City Size, Urbanization, Brazil.

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1 Introduction

Landslide events are increasing worldwide, driven by climate change and quickly and disorderly urbanization. This is a critical concern for developing countries, which account for 80% of global fatal landslides (Froude and Petley, 2018) and are more vulnerable, mainly due to the proliferation of informal settlements in hillside areas (Ozturk et al., 2022), and the absence of efficient disaster risk management policies. Although it is well documented that urban growth increases susceptibility to landslides (Rohan et al., 2023), little is known about the consequences of landslides on subsequent urbanization patterns. On the one hand, landslides can be a pull force for urbanization: the destruction of infrastructure and buildings triggered by landslides can be seen as a major opportunity for reconstruction and elimination of frictions that impede urban development (Hornbeck and Keniston, 2017). On the other hand, landslides can be a push-down force for urbanization: their destructive potential can generate large economic losses that discourage new construction, avoid rebuilding, and increase the overall perceived risk.

This paper aims to shed light on this question by examining the causal impact of landslides on subsequent urbanization patterns in Brazilian cities and, additionally, analyzing the underlying mechanisms that explain this potential relationship. Our analysis focuses on two alternative dimensions of urbanization: the urban area size and a fragmentation index calculated as the average proportion of undeveloped land surrounding urban grids in the spirit of Burchfield et al. (2006). The urban area size is a crucial measure of the overall extent of the urban agglomeration, being widely adopted as a proxy for city size in urban economic models (Duranton and Puga, 2015). The fragmentation index captures the city's urban form and is a key indicator of sprawl, which directly influences overall well-being (Nechyba and Walsh, 2002).

Brazil offers a unique setting to examine this question. Firstly, the country is one of the ten countries most exposed to landslides in the world, both in terms of the size of the affected territory and the total number of fatalities (Robson, Radulescu and Petley, 2022). Landslides are a recurrent phenomenon in Brazil[1] and from 2003 to 2020, these events affected 554 cities in the country, directly impacting 921 thousand individuals and resulting in the loss of 6827 lives (Veloso et al., 2022). Secondly, Brazilian cities present significant imbalances in land-

[1]In Brazil, landslides are disasters that predominantly affect urban areas and are characterized by soil and mud movements that occur in high-slope regions and are usually triggered by heavy rainfall. Landslides occurrence in Brazil is strongly linked to human settlements in disaster-prone areas (da Silva, Marengo and Ruv Lemes, 2024). These settlements are disorderly established, often without government regulation, and are associated with precarious drainage systems, deforestation, and erosion, factors that increase the susceptibility to landslides.

use patterns, geography, and socioeconomic structure. This creates a natural variability in landslide exposure across cities and allows us to estimate the general effect of these disasters rather than evaluate the effect of a large and single event. By using this approach, we ensured greater external validity for our results.

In this way, our research design takes advantage of the variation of landslide events in temporal and geographic dimensions and compares the evolution of urbanization in affected municipalities (treated group) with that in unaffected municipalities (control group), using the staggered Difference-in-Differences approach developed by Callaway and Sant'Anna (2021). In our main analysis, we used two alternative control groups: one formed by all never-affected municipalities and a more restricted one formed by never-affected municipalities, but which have a high risk of experiencing landslides[2]. Our main database consists of a yearly municipality-level panel spanning from 2003 to 2020. To build this database, we combined data from landslide records compiled by Veloso et al. (2022), high-resolution satellite data identifying urban land use gathered by the MapBiomas Project, housing finance variables collected by the Brazilian Central Bank, and a set of socioeconomic and land policy data from the Brazilian Institute of Geography and Statistics (IBGE).

Our results show that landslides cause an average reduction of 8.71% (6.45% with the matched control group) in the urban area size of the affected municipalities. This effect occurs immediately after the shock and persists in the following years with an intensification, suggesting that landslides are an important push-down force of urban agglomeration in Brazilian cities. Furthermore, our findings also reveal that the landslide shocks persistently increase the average fragmentation index of affected cities, indicating that these disasters can also modify the urban shape. In this way, landslides result in a smaller and more fragmented urban area. These results remain robust to alternative control groups, empirical specifications, different estimators, and alternative inference procedures. Finally, we also investigated whether the landslides can drive changes in the urbanization patterns of non-affected cities that border those directly affected, but we do not find evidence of this type of spatial spillover.

Then, we investigate the underlying mechanisms that can explain the relationship between landslides and the spatial size of urban areas. Initially, the damages caused by landslides can induce a negative economic shock and contribute to population decline through increased out-migration rates. As established by the standard monocentric urban model, income and population size are the main drivers of the aggregated housing demand and,

[2]This control group is constructed using propensity score matching which selects non-affected cities with comparable observable landslide risk factors (including climatic, topographic, and socioeconomic variables) to those affected by landslides.

consequently, urban land consumption (Brueckner and Fansler, 1983). Thus, negative shocks to income and population tend to result in smaller urban areas (Paulsen, 2012; Deng et al., 2008). Our results indicated that although landslides do not affect the population size, they can trigger a slowdown in the economic activity of affected municipalities, sharply reducing the stock of housing loans. We also present suggestive evidence that landslide shocks lead to a decline in the local housing market. Municipalities exposed to landslides experienced a reduced housing stock compared to those unaffected, particularly in single-family housing units and homes with adequate infrastructure.

Secondly, natural disasters can encourage the implementation of more stringent land-use regulations by local governments as an adaptative response to mitigate damage from future disasters (Ostriker and Russo, 2022; Burby and Dalton, 1994), which also tends to limit the spatial size of cities (Bertaud and Brueckner, 2005; Brueckner and Sridhar, 2012). We evaluated this mechanism but found no evidence that landslides trigger greater adoption of land use controls by affected cities, including zoning ordinances, lot subdivision laws, building codes, or urban growth boundaries. Thus, our findings support the hypothesis that lower income and the consequent lower local housing market size may be the main mechanism explaining the negative effect of landslides on urbanization patterns.

Our paper is closely related to the literature investigating the consequences of extreme weather events and natural disasters on urbanization patterns (Siodla, 2015; Martinez and Magontier, 2023; Xu and Wang, 2019; Castells-Quintana, Krause and McDermott, 2021; Henderson, Storeygard and Deichmann, 2017). In general, the evidence indicates that cities affected by natural disasters or adverse climate shocks experience an *increase* in subsequent urbanization. Different reasons explain this result. Firstly, disasters are an opportunity to eliminate frictions that impede urban redevelopment, such as old buildings and obsolete infrastructures that are costly to relocate or remove (Siodla, 2015). Secondly, extreme weather events may encourage rural-urban migration to manufacturing cities as agricultural incomes tend to fall due to weather shocks (Henderson, Storeygard and Deichmann, 2017). Finally, disasters can stimulate the adoption of adaptive responses that can improve the attractiveness of the affected region, such as improvements in maintenance and livability conditions, stimulating new urban developments (Martinez and Magontier, 2023).

We contribute to the literature discussed above in two distinct ways. Firstly, our paper is unique in investigating the effect of landslides on subsequent urbanization patterns. Unlike events studied in previous studies (such as climate shocks, floods, and fires), landslides have a greater capacity to destroy houses, buildings, and urban infrastructure as they permanently alter the geomorphology of the soil. This particularity can make the dynamics of post-disaster urbanization and adaptive policies different from other shocks. Secondly, our paper shows in a pioneering way that the decline of the local housing market (measured by the volume of housing loans) is a key mechanism to explain the negative impacts of disasters on the size and shape of urban areas. This evidence points out that shifts in the local housing market and the corresponding increase in the overall perceived risk in the aftermath of disasters are a way to drive cities to their optimal size and correct inefficiencies in the spatial distribution of urban land use.

Our paper is also related to a broader literature that evaluates the impact of natural disasters on the spatial distribution of population and economic activity across cities. Evidence shows that major disasters can permanently affect the trajectory of population growth (Ager et al., 2020; Dottori, 2023; Husby et al., 2014; Kim and Lee, 2023), and the spatial distribution of employment (Barsanetti, 2023) and reduce the economic performance of affected cities (Elliott, Strobl and Sun, 2015; Boustan et al., 2020; Aguirre et al., 2023). Our paper contributes to this literature by showing that the negative shock adjacent to natural disasters can generate consequences that surpass the reduction of population and local income, permanently changing the urbanization path and the overall shape of impacted cities.

The remainder of the paper is organized as follows. In Section 2, we present the data sources, describe the variables, and discuss the construction of our main sample. Additionally, we highlight the local characteristics that explain the spatial distribution of landslides in the Brazilian territory. Section 3 presents our research design. In Section 4, we present the main results and robustness tests. In Section 5, we provide a detailed discussion of the mechanisms that explain the relationship between landslides and urbanization patterns. Finally, Section 6 concludes the paper.

2 Data and Descriptive Statistics

In this section, we will outline the process of collecting data, the definitions of the variables, and the sample construction based on a municipality-year panel dataset. Additionally, we will present some descriptive statistics comparing the characteristics of municipalities exposed to landslides with the non-exposed ones.

2.1 Data Sources and Variable Definitions

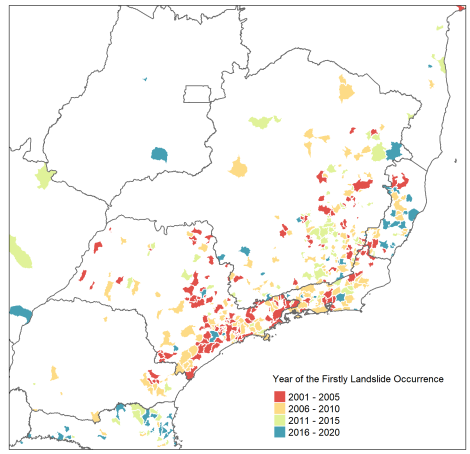
Landslides Records. The most comprehensive and up-to-date database on natural disasters in Brazil has been compiled by Veloso et al. (2022). The authors gathered information from a variety of primary data sources, including the Integrated Disaster Information System (S2ID) managed by the Brazilian Ministry of Regional Development, the Brazilian Institute of Geography and Statistics (IBGE), and the Atlas of Human Development. This database provides monthly information at the municipal level and covers the period from January 2003 to February 2021. In addition to landslide disasters, this database includes data on various other types of events, such as floods, flash floods, droughts, inundations, frosts, storms, windstorms, and barrier collapses. For each type, it provides details on the number of affected individuals categorized as injured, displaced, homeless, or deceased. According to this database, there were 556 primary[3] landslides recorded in Brazil during our study period (2003 to 2020), significantly surpassing the number documented in other international disaster databases, such as EM-DATA (which reports 6 records from 2003 to 2019) and the Global Fatal Landslides Database – GFLD (which documents 136 records from 2004 to 2016). This difference comes from the fact that EM-DATA captures data on large-scale events, and the GFLD focuses solely on fatal landslides, while the compilation of events by Veloso et al. (2022) includes all sorts of registrations such as tabulations, media reports, and other sources. Our research offers a higher frequency event analysis of how these natural disasters impact urban patterns by obtaining a more comprehensive database of landslides. To provide insight into the data, Figure 1 shows how landslides occur across time and space in Brazil. Figure 1a presents the geographic distribution of landslides in the whole Brazilian territory, Figure 1b presents the geographic distribution zooming in on the Southeast region and highlighting the year of occurrence of each landslide, and, finally, Figure 1c shows the evolution in the number of events throughout the years. It is possible to observe two stylized facts regarding the occurrence of landslides in Brazil: they are geographically concentrated in the southeast region (which accounts for 70.58% of all events) and they are events that occur with a strong recurrence and variability over time.

Urbanization Patterns. We will use two dependent variables to measure the patterns of urbanization in Brazilian cities: the urban area size and an index that measures the degree of fragmentation of the urban form. Both variables are constructed using satellite data extracted from the MapBiomas platform (MapBiomas, 2024). This platform has been collecting annual images of land use in raster format from the Landsat satellite since 1985 and, using machine learning techniques, classifies the land of Brazilian territory into different uses, including urban infrastructure, forest formation, pasture, mining, hydrological use, and a wide variety of natural uses that vary according to the types of biomes in Brazil. Based on these annual raster images, we divided the Brazilian territory into 1km x 1km grids to calculate our two outcome variables at the municipality-year level. Our primary outcome is

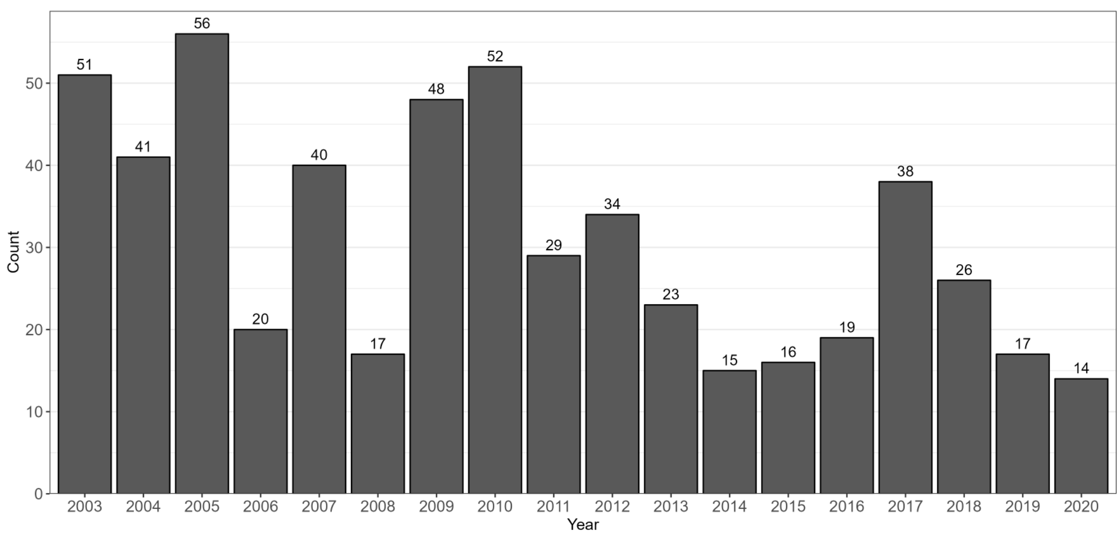
[3]Our research will focus on understanding the consequences of primary landslides, defined as the initial landslide event that impacts a given municipality. This focus is important because primary landslides permanently alter the geomorphology of the soil, potentially resulting in long-lasting consequences.

Figure 1: Descriptive Analysis of Landslides

(a) Spatial Distribution of Landslides



(b) Landslides in the Southeast



(c) Annual Occurrence of Landslides

Note: Figure A presents the spatial distribution of landslide events in Brazilian territory. Figure B zooms in on the southeast region, showing landslides and their year of occurrence. Figure C presents the yearly evolution of primary landslide numbers from 2003 to 2020.

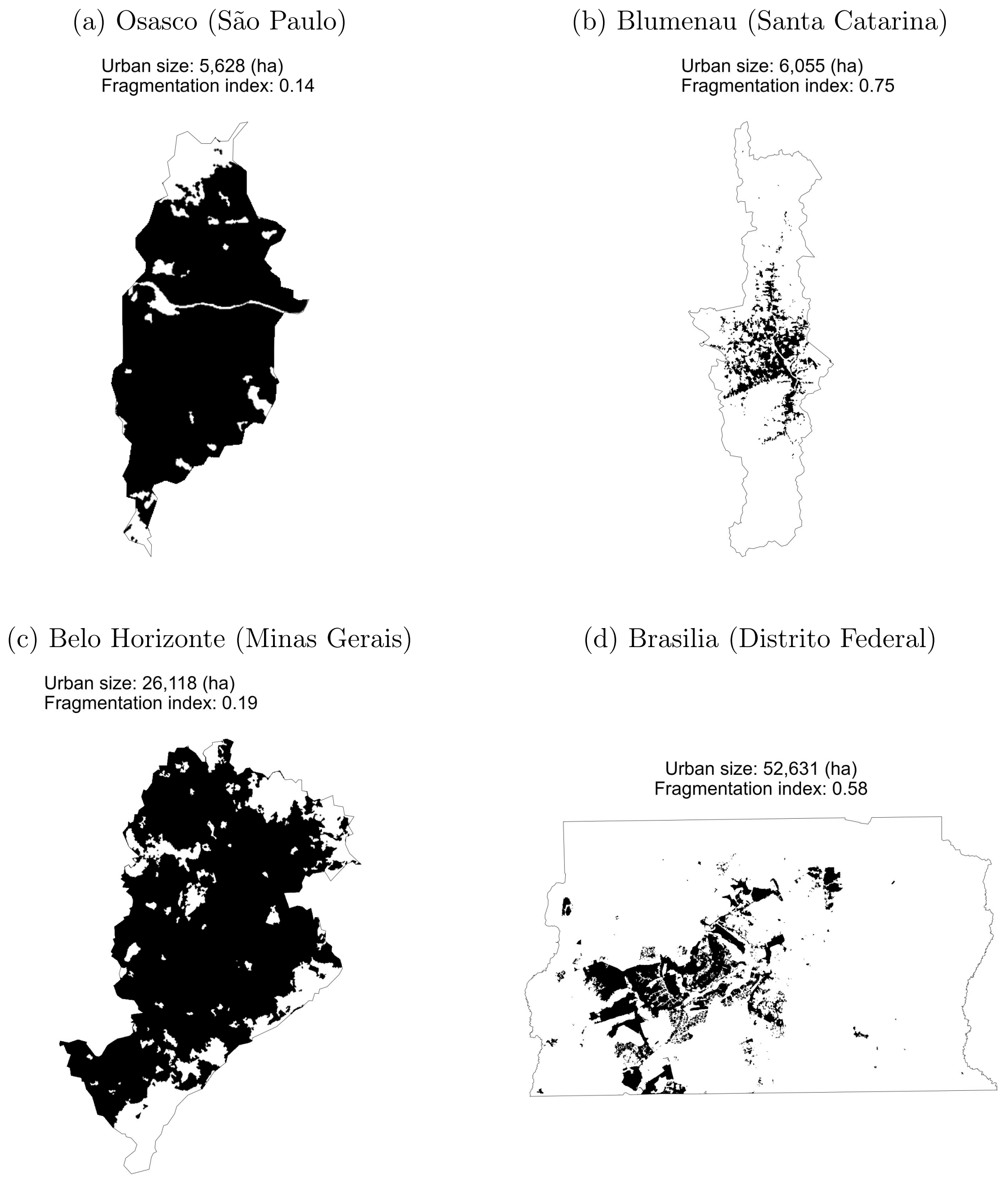
the urban area size in hectares. This variable is calculated by summing the built-up areas between the different grids within the initial municipal border[4]. Our secondary outcome is the fragmentation index, which is constructed similarly to the sprawl index developed by Burchfield et al. (2006). More specifically, we first identify grids with some degree of urbanization and then calculate the percentage of undeveloped land in each 1km x 1km grid. Thus, our fragmentation index is defined as the average proportion of undeveloped land in the different square kilometer urban grids that compose the municipality[5]. Therefore, this index ranges from 0 to < 1, so that the closer it is to one, the greater the fragmentation of urban occupation. It is worth noting that this index captures the scatteredness of urban development, which is just one aspect of urban sprawl. To provide a clearer idea of our outcome variables, Figure 2 illustrates the urban area size measured in 2010 for two medium-sized cities (Osasco and Blumenau) and two large cities (Brasília and Belo Horizonte). Visually, it is evident that Osasco and Belo Horizonte have more compact and less scattered built-up areas, leading to low fragmentation indexes (0.14 and 0.19, respectively). In contrast, Blumenau, and Brasília exhibit more spread-out layouts, resulting in higher fragmentation indexes (0.75 and 0.58 respectively).

Economic Outcomes. To investigate the potential mechanisms that explain the relationship between landslides and urbanization patterns, we incorporated into our database the following variables at the municipal-year level: GDP per capita, population size, and housing loan stock. The GDP and population size are calculated by the Brazilian Institute of Geography and Statistics (IBGE). Since 1999, the IBGE has consistently calculated the municipalities' GDP. However, the population count is conducted only during the demographic census, which occurs approximately every ten years. However, IBGE provides annual data on the projected population size by municipality. Finally, the stock of housing loans was sourced from the *Estatística Bancária Mensal por Município* (ESTBAN) of the Brazilian Central Bank. This platform has provided monthly data at the municipal level since 1988, encompassing various financial items, including the stock of housing loans. Given that a significant proportion of municipalities (40% of our sample) had no stock of housing loans, we will measure this variable in two alternative ways: as a dichotomous variable, where 1

[4]The advantage of this procedure is maintaining the consistency of municipal borders over time, allowing us to track the temporal variation of the urban areas without being influenced by changes in the political-administrative borders of the municipalities.

[5]The sprawl index of Burchfield et al. (2006) is defined as *"the percentage of undeveloped land in the square kilometer surrounding an average residential development"*. Therefore, despite being similar, the calculation of our index has two differences. Firstly, our index is calculated on previously defined one square kilometer grids, while in the index of Burchfield et al. (2006) the reference grid area is established based on residential development cells. Furthermore, our index considers any urban development, while that of Burchfield et al. (2006) only considers residential development.

Figure 2: The Urban Layout of Selected Brazilian Cities



Note: This figure displays the urban area, including information on the size and fragmentation index, for two medium-sized cities (Osasco and Blumenau) and two large cities (Belo Horizonte and Brasília).

indicates the presence of housing loans in the municipality-year, and as a continuous variable representing the value of the loan stock.

Land-Use Regulations. We will also evaluate whether the adoption of land-use regulations by local governments as a response to landslides is an underlying mechanism. Information on land-use regulations was extracted from the *Pesquisa de Informações Básicas Municipais* (MUNIC), a survey conducted almost annually by IBGE to gather information on the structure, dynamics, and functioning of local governments in Brazil. In this survey, mayors of Brazilian municipalities are asked about a set of policies currently implemented in their jurisdictions. In some specific years, information is collected regarding the adoption of land-use regulations and the year the respective regulation was implemented[6]. Using the 2018 survey, it is possible to track the year the regulation was initially adopted or revised in each specific municipality and construct land-use indicator variables in a yearly municipality panel format. More specifically, we constructed four indicator variables that assume one (and zero, otherwise) in the years that municipalities are adopting the following land-use regulations that potentially affect the local urban growth: zoning ordinance, urban growth boundary, land subdivision law, and building code[7]. An important shortcoming of these data only indicates the presence or absence of regulations, not their stringency. Table A.1 in the Appendix summarizes the variables used throughout the paper, including their definitions, sources, and periodicity.

2.2 Sample Selection

By combining these data, we construct a municipality-year panel dataset containing the universe of 5,515 Brazilian municipalities for a period ranging from 2003 to 2020. To evaluate the effects of landslides, we will compare the trajectory of the evolution of the urban area size and the fragmentation index between the affected municipalities (defined as the treatment group and composed of 556 municipalities) and the municipalities that were never affected (control group, composed of 4,459 municipalities). Although our main sample is formed of these two groups without any restrictions, some problems may arise due to initial differences between the characteristics of the affected and unaffected municipalities.

[6] In 2004, 2005, 2008, 2009, 2012, 2013, 2015, and 2018, information on land-use regulations was collected in the MUNIC survey. However, only in the 2013, 2015, and 2018 surveys, the adoption year is also collected.

[7] Zoning ordinances govern land use by designating specific areas for residential, commercial, or industrial purposes, while also setting limits on maximum building heights. Urban growth boundaries are put in place to curb urban fragmentation, preserving green spaces and agricultural land. Land subdivision laws impose minimum lot sizes and other requirements to manage the division of land into smaller parcels, preventing excessive density. Additionally, building codes establish standards for construction practices and materials, ensuring the safety and durability of structures.

As well documented in the literature on geological disasters, susceptibility to landslides tends to be higher in areas with informal settlements, and more urbanized areas, which have more rugged reliefs and are commonly affected by heavy rains. (da Silva, Marengo and Ruv Lemes, 2024; Samia et al., 2017; Wang, Lin and Shi, 2018). This can generate an initial imbalance in geographic and socioeconomic characteristics between the municipalities that form the treatment and control groups. Although this potential imbalance does not directly violate our identification hypothesis, it can lead to divergences in the pre-shock urbanization trajectory between different groups of municipalities, making it difficult to identify a causal effect. To address this potential shortcoming, we also consider an alternative sample in which the control group comprises only municipalities that have never suffered landslides but have a high risk of being affected.

More specifically, we performed pre-processing matching on our main sample to select municipalities from the control group with landslide risk characteristics similar to the affected municipalities (Ho et al., 2007). This is done by applying a propensity score matching (PSM) that uses the nearest neighbor algorithm and considers the following baseline variables that were measured in 2000: average altitude, terrain roughness index, average precipitation separated by season, average temperature by season, population size, income per capita, urbanization rate, the share of informal settlements, urban area size, and the fragmentation index[8]. Table B.1 in the Appendix shows the balance check comparing the mean values of the treatment and control group characteristics before using the PSM and after using the PSM[9]. It is noted that this procedure generates a significant balance between municipalities exposed and not exposed to landslides, which reduces our concerns about the initial imbalance. Therefore, we will also use this matched sample in our estimations, which will consist of 556 treated municipalities and 556 control municipalities.

2.3 Summary Statistics

Table 1 presents the summary statistics for two specific years in our panel database: the initial year (2003) and the final year of the analysis (2020). The means and standard deviations (in parentheses) of our main variables are separated into three different groups: treated municipalities (those affected by landslides at some point), control municipalities,

[8]Precipitation and temperature variables by season are obtained through the aggregation at the municipality level of 0.5km x 0.5km grid data from the University of East Anglia's Climatic Research Unit (Harris et al., 2014). The socioeconomic variables are obtained from the 2010 Brazilian Demographic Census collected by the IBGE.

[9]This test provides important insights into the potential determinants of landslides. Compared to unaffected municipalities, those impacted by landslides have more rugged terrain, higher altitudes, greater rainfall rates, larger populations, and urban areas, higher income, and higher levels of urbanization.

and matched control municipalities.

Table 1: Summary Statistics

	Pre-Treatment Period (2003)			Post-Treatment Period (2020)		
	Treated	Control	Matched Control	Treated	Control	Matched Control
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Urban Area Size)	5.9	4.77	5.62	6.27	5.25	6.04
	(1.71)	(1.2)	(1.66)	(1.62)	(1.1)	(1.56)
Fragmentation Index	0.785	0.832	0.806	0.757	0.796	0.774
	(0.152)	(0.09)	(0.116)	(0.159)	(0.0932)	(0.121)
ln(Population)	10.3	9.17	10	10.4	9.28	10.1
	(1.47)	(0.97)	(1.27)	(1.52)	(1.02)	(1.35)
ln(GDP per Capita)	2.47	2.14	2.4	2.71	2.46	2.65
	(0.639)	(0.66)	(0.676)	(0.605)	(0.642)	(0.6)
ln(Stock of Housing Loans)	10.3	3.99	9.75	18.2	14.4	17.2
	(9.09)	(7.27)	(9.03)	(6.57)	(8.04)	(7.46)
Housing Loans (0/1)	0.568	0.234	0.544	0.9	0.774	0.856
	(0.496)	(0.42)	(0.499)	(0.3)	(0.418)	(0.351)
Zoning Ordinance (0/1)	0.272	0.155	0.269	0.822	0.62	0.783
	(0.445)	(0.36)	(0.444)	(0.383)	(0.485)	(0.412)
UGB (0/1)	0.304	0.266	0.259	0.964	0.888	0.949
	(0.46)	(0.44)	(0.439)	(0.186)	(0.316)	(0.22)
Land Subdivision (0/1)	0.189	0.124	0.195	0.77	0.59	0.695
	(0.392)	(0.33)	(0.397)	(0.421)	(0.492)	(0.461)
Building Code (0/1)	0.448	0.316	0.463	0.793	0.655	0.785
	(0.498)	(0.465)	(0.499)	(0.405)	(0.475)	(0.411)
Number of Municipalities	556	4459	556	556	4459	556

Note: The table shows the mean and standard deviation (in parenthesis) for 2003 and 2020. These summary statistics are separated into three groups of municipalities: those affected by landslides (treatment group), those never-affected (control group), and those never-affected with a high risk of experiencing a landslide (matched control group).

Initially, it is possible to note that the affected municipalities (column (1)) are relatively comparable to the control municipalities (column (2)), showing minor differences in terms of urban area size, fragmentation index, population size, and GDP per capita. However, the municipalities impacted by landslides tend to be slightly larger and more urbanized on average. Additionally, this group experiences a higher volume of housing loans and greater adoption rates of land-use regulations. Furthermore, the comparison between standard deviations reveals that the distribution of variables in the group of control municipalities is much more uniform. After carrying out the PSM, it is observed that the average differences between the treatment group (column (1)) and the control group (column (3)) dropped significantly, reinforcing that the pre-processing matching was effective in reducing the initial imbalance between the two groups. Comparing the evolution of variables between 2003 and 2020 in Table 1, it is possible to notice that Brazilian cities became larger, less fragmented, with larger housing credit systems, and began to adopt land-use regulations more intensely.

3 Empirical Strategy

To estimate the impact of landslides on the urbanization patterns of Brazilian municipalities, we take advantage of the variation of events in the geographic and temporal dimensions and compare the evolution of the outcomes of the affected municipalities (treatment group) with the corresponding evolution of similar non-affected ones (control group) using a Difference-in-Differences (DiD) approach. Considering that we have variations in treatment timing since landslides hit the municipalities in different years, a standard estimate of DiD using the two-way fixed effects (TWFE) estimator is biased and does not recover in easy-to-interpret causal parameters. As pointed out by Goodman-Bacon (2021), the TWFE estimator generates problems of negative weights associated with misleading comparisons between already-treated and late-treated units.

Although there is a wide variety of recent proposed robust DiD estimators (See Roth et al. (2023) for a review), we will adopt the estimator proposed by Callaway and Sant'Anna (2021) because it adapts well to our research context in the sense that it allows for group-time heterogeneities and a staggered design. It should be noted that the local response to landslides is expected to change over time due to the introduction of new technologies and the implementation of new regulatory frameworks, which can result in potential heterogeneity between groups of municipalities affected in different years[10]. Additionally, landslides tend to generate permanent changes in the shape and geomorphology of the affected area, since it is not feasible to completely remove the debris flows and restore the previous city landscape. In this sense, it is reasonable to assume that there is no possibility of a municipality being "unexposed" after experiencing a landslide, giving us a staggered adoption scheme.

The estimator developed by Callaway and Sant'Anna (2021) considers that the effect of treatment on the treated (ATT) may differ between treatment groups or cohorts g and over time t and, therefore, proposes the group-time ATT, denoted by $ATT(g, t)$. In this approach, each treated municipality i can be classified into a cohort $G_i = g \in \{2003, \dots, 2019\}$ according to its first year of exposure to landslides, denoted by g. Thus, the average effect of landslide in group g of municipalities at time $t \geq g$ can be semi-parametrically estimated by the following expression:

[10]In Appendix C.1, we report the group-specific ATTs and confirm that there is strong heterogeneity in the effect of landslides between groups of municipalities that were exposed in different years.

$$\widehat{ATT}(g,t) = \frac{\sum_i (y_{it} - y_{ig-1})\, 1\{G_i = g\}}{\sum_i 1\{G_i = g\}} - \frac{\sum_i (y_{it} - y_{ig-1})\, 1\{C_i = 1\}}{\sum_i 1\{C_i = 1\}} \tag{1}$$

Where $(y_{it} - y_{ig-1})$ is the difference in the outcome of municipality i between year t and one year before the municipality experiences the first landslide, $g - 1$. The term $1\{G_i = g\}$ is an indicator variable that assumes 1 if unit i is firstly treated in year g and $1\{C_i = 1\}$ is an indicator variable that assumes 1 for municipalities that have never been exposed to landslides. The estimator of equation (1) resembles a two-period/two-group DiD estimator, as it compares the evolution of the outcome of group-specific treated municipalities (first term on the right side) with the evolution of the outcome of the control group (second term on the right side) within the same time interval.

After estimating equation (1), we obtain 272 group-specific ATTs, since we have 17 time periods and 16 municipalities cohorts[11]. To summarize these group-time ATTs and investigate the dynamic effect of landslides, we followed the aggregation proposed by Callaway and Sant'Anna (2021) and presented the main results as event study plots in which we computed the (weighted) average of the group-time ATTs at different lengths of exposure to the treatment L using the following expression:

$$\widehat{ATT}^{w}_{L} = \sum_g w_g ATT(g, g+L) \tag{2}$$

Where the weights w_g are defined as the frequency of cohorts of treated municipalities g in relation to the set of all treated municipalities. In addition to the event study plots, we summarize post-treatment ATTs into a single measure to get an overall treatment effect on the treated. For inference, we constructed 95% confidence intervals using the multiplier bootstrap procedure suggested by Callaway and Sant'Anna (2021) and clustered the standard errors at the municipality level.

Two assumptions must be satisfied to identify the group-time ATT: the parallel trends assumption and the limited treatment anticipation assumption. The parallel trends assumption sets that the urbanization trajectory of the group g of municipalities that was exposed between $g - 1$ and t would be the same urbanization trajectory of the unaffected cities in the hypothetical absence of landslides. Although Callaway and Sant'Anna (2021) relaxed this assumption to allow for parallel trends conditional on observed covariates, we believe that unconditional assumption will suffice in our application. As shown in subsection 3.3, we performed pre-processing matching that selected a control group similar to the treated

[11] We removed the 51 municipalities treated in the first year of our database because we cannot track their pre-treatment.

ones in the observable dimension. The assumption of limited treatment anticipation posits that the treatment path is not previously known, and the units cannot choose their treatment status. We believe that this assumption holds in our context because landslides are intrinsically unexpected and uncertain phenomena, over which humans have limited control (Yang et al., 2022). In any case, the credibility of both identification assumptions can be empirically checked by analyzing the pre-treatment effects in our event study.

4 The Effect of Landslides on Urbanization Patterns

4.1 Main Results

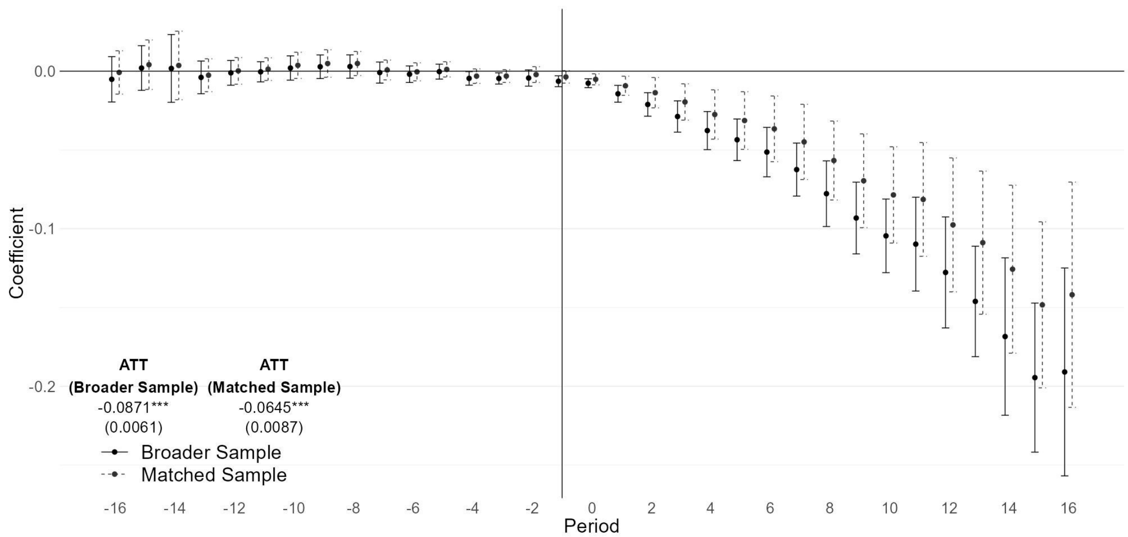
Figure 3 shows the results of the event studies based on equation (2) which aggregates the group-time ATTs. We present the results considering two alternative control groups: a broader one that considers all never-affected municipalities in Brazil and a more restricted one, that only considers never-affected municipalities with a high risk of suffering a landslide (matched sample). Figure 3a shows the effect of landslides on the log of urban area size and Figure 3b shows the effect of landslides on the fragmentation index of the urban area. In addition to the event study plots, we also report the overall post-treatment ATTs.

From Figure 3a, we note that landslides cause an immediate reduction in the urban area size of the affected municipalities and that this effect reduces significantly over time, with strong persistence. The overall ATT shows that landslides generate, on average, a reduction of -6.45% to -8.71% in the urban area size across the year of the shock and sixteen years after exposure to the event. In both specifications there is no evidence of a pre-treatment trend, suggesting that the identifying assumptions of the staggered Difference-in-Differences hold in our setting. This also shows that before the landslides occurred, the urbanization pattern of the municipalities that would be affected did not differ from the urbanization pattern of the unaffected municipalities, indicating that a reverse causality between urbanization and landslides cannot explain our result. As Goodman-Bacon and Marcus (2020) shows, checking the pre-treatment trends can also be used as a direct test for reverse causality.

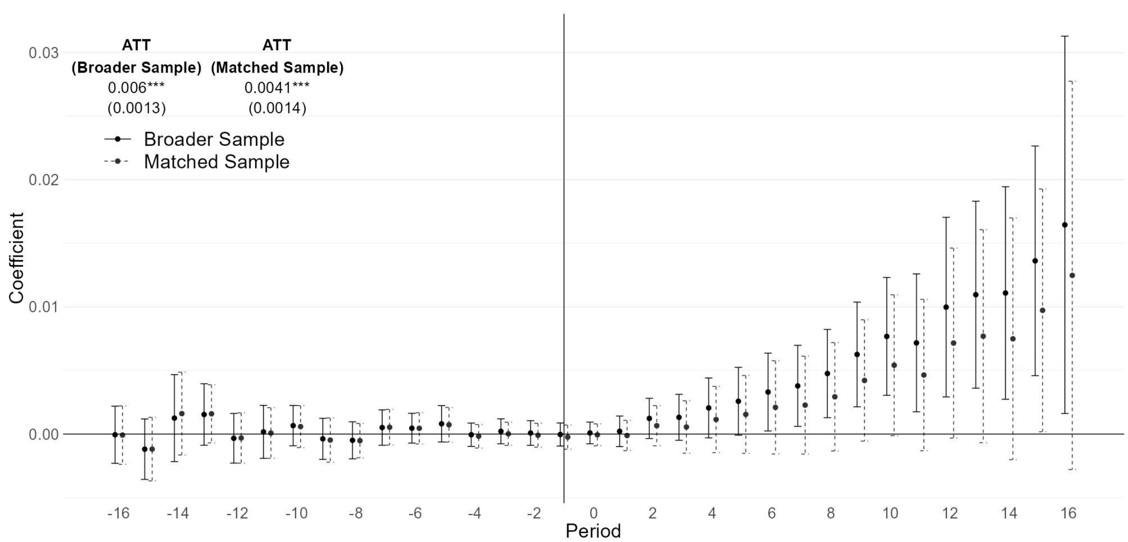
In general, estimates using the broad and matched control group are very similar, with the latter providing slightly imprecise confidence intervals. Figure 3b shows that municipalities affected by landslides experience an increase in the degree of fragmentation of their urban area. The effect only begins to appear in the fifth year after the event considering the broader control group and persists even after sixteen years of exposure. The overall ATT indicates that landslides cause, on average, a 0.004 to 0.006 increase in the fragmentation index of the affected cities. These effects correspond to increases of 0.51% and 0.77% in

Figure 3: Landslides Effects on Urbanization Patterns

(a) Urban Area Size



(b) Fragmentation Index



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figure D.2a presents the results for the log of urban area size and Figure D.2b for the fragmentation index. In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

relation to the average fragmentation index, respectively. Lastly, we also found no evidence of a pre-treatment trend for this specific outcome in both specifications.

The immediate reduction in the urban area shown in Figure 3a as a response to the shock is expected since landslides usually happen in consolidated urban zones and cause the direct destruction of settlements located on the slopes that have collapsed. However, the increasing magnitude of this effect over time and its strong persistence suggest that there is something more at play that cannot be directly explained by a simple destructive effect of the landslide shock. In section 5, we will try to understand the underlying mechanisms that can explain this result. Viewed together, the evidence in Figures 3a and 3b indicates that landslides are a push-down force for urban agglomeration since they result in smaller and more fragmented urban areas. If we interpret this as a new long-term equilibrium, landslides can be seen as an event that corrects inefficiencies in the spatial distribution of urban land use and drives cities toward their optimal size.

4.2 Robustness Checks

In Appendix D we present the details and the estimations of a broad set of robustness checks of our main results. More specifically, we adopt the following changes to our main result: used a control group formed by municipalities that have not yet been treated (D.1), restricted our sample to municipalities in the southeast region (D.2), restricted our sample to municipalities classified as having a high level of disaster risk by the government (D.3), removed municipalities exposed to floods and droughts from our analysis (D.4), used other DiD-Robust estimators (D.5), alternative inference procedures (D.6) and, finally, we evaluated the possibility of spatial spillovers arising from landslide shocks (D.7). Table D.1 in the Appendix presents the post-treatment ATT estimates for both the baseline and robustness estimates to provide a summarized overview of the robustness tests. Overall, the results in section 4.1 are quite robust.

5 Mechanisms

Our findings show that landslides cause a persistent reduction in urban area size and increase the urban fragmentation of affected cities. Moreover, we noted a significant rise in the magnitude of these effects over the exposure period, suggesting that the relationship between landslides and subsequent urbanization cannot be solely explained by the direct destruction of urban infrastructure caused by the disaster itself. In this subsection, we will evaluate two alternative mechanisms that can explain these results: the possible variation in income, population, and housing demand triggered by the landslides and the increase in the incidence of land-use regulations by the local governments.

5.1 Income Shocks, Population and Housing Loans

Landslides may have led to a lasting reduction in the city's urban area by causing a negative income shock, displacing the population, and weakening the local housing market. Some predictions from the standard monocentric model support this hypothesis. Firstly, in the closed-city version of the model, the city's spatial size is determined by local income, population size, commuting costs, and the value of agricultural land[12] (Brueckner and Fansler, 1983). Income and population variations play similar roles in determining the physical city size, as they are the primary factors driving housing demand and, consequently, urban land consumption. Several studies have empirically corroborated these predictions for different contexts (Paulsen, 2012; Deng et al., 2008; Spivey, 2008; McGrath, 2005).

Additionally, natural disasters are often viewed as negative income and population shocks. The physical destruction they cause increases overall perceived risks and harms local establishments, leading to economic slowdowns and changes in the spatial distribution of economic activity (Elliott, Strobl and Sun, 2015; Boustan et al., 2020; Aguirre et al., 2023; Lima and Barbosa, 2019). Moreover, out-migration is a common adaptive response to such climate disasters, often resulting in a smaller local population (Ager et al., 2020; Dottori, 2023; Kim and Lee, 2023). Therefore, since urban areas usually shrink when cities experience income and population shocks that lower housing demand, and because natural disasters can trigger such shocks, landslides likely have negative and lasting effects on the urban layout of affected cities.

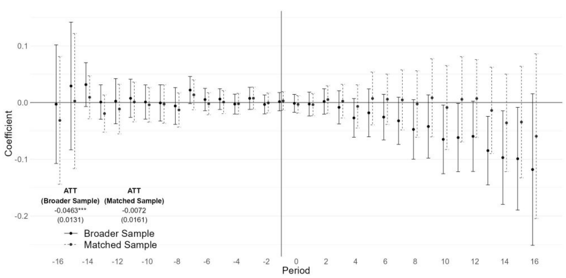
To investigate if this mechanism makes sense in our context, we investigated the impact of landslides on GDP per capita, population size, and the volume of housing loans (which can

[12] These two last mechanisms will not be evaluated because we do not have comprehensive data in Brazil that measures the price of agricultural land and commuting costs at a municipal-year level.

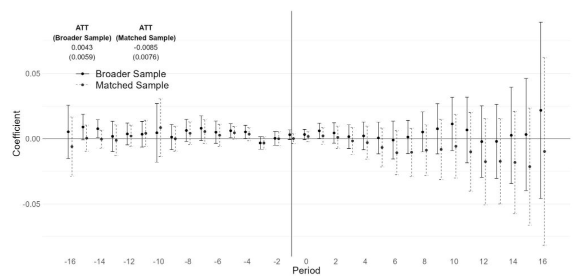
be seen as a proxy for the size of the local housing market) using our staggered Difference-in-Differences approach. Figure 4 shows the event study plots. As several municipalities have no stock of housing loans (e.g., 71% of municipalities not treated in 2003, as described in Table 1), the distribution of this variable is very left-skewed and the landslides can also affect the extensive margin. For this reason, we estimate the impact of landslides on the extensive margin in Figure 4c and on the intensive margin in Figure 4d. In the first case, the dependent variable is a dummy that assumes 1 when there is some housing loan in the municipality and assumes 0, otherwise. In the second case, the dependent variable is the log of the housing loan value + 1.

Figure 4: Landslides Effects on GDP per Capita, Population and Housing Demand

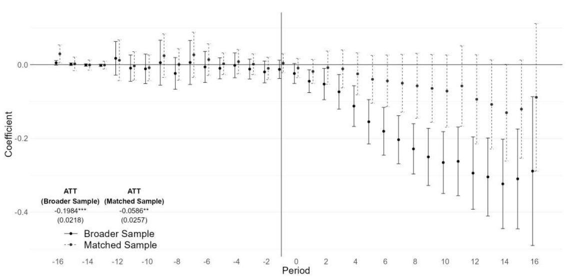
(a) Log of GDP per Capita



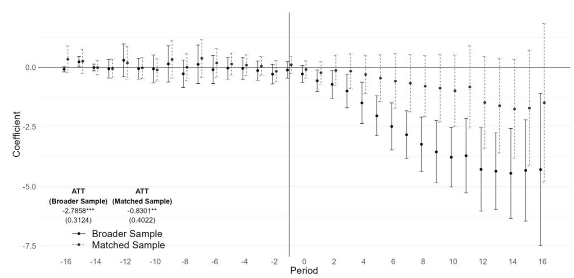
(b) Log of Population Size



(c) Dummy of Housing Loan - Extensive Margin



(d) Log of Stock of Housing Loan - Intensive Margin



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figure 4a presents the results for the log of GDP per Capita, Figure 4b for the log of Population, Figure 4c for the extensive margin of housing loans and 4d for the log of the Stock of Housing Loans (In Brazilian R$). In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

Figure 4a shows that municipalities exposed to landslides presented an average reduction in GDP per capita of 4.63%, indicating that an economic slowdown characterizes the post-disaster period. Although this result is not robust when using the matched sample, additional evidence presented in Appendix E shows that municipalities affected by landslides experience significant reductions in average wages, employment, and the number of establishments. These auxiliary findings strengthen our confidence that landslides can be considered a negative income shock to the local economy. Figure 4b shows that, in both specifications, the population dynamics of the municipalities affected by the landslides are not changed by the shock. In relation to housing stock loans, we note that landslides generate a sharp reduction in the extensive margin (Figure 4c): the affected municipalities reduce the probability by -19.94% (-5.86% for the matched sample) of having housing stock loans after the disaster compared to those not affected. The results from the intensive margin (Figure 4d) practically reproduce those from the extensive margin. However, as the treatment directly affects the extensive margin, the log-like coefficients have a problematic interpretation (Chen and Roth, 2024). The sharp decline in housing loans in combination with the economic slowdown in municipalities exposed to landslides indicate that such shocks weaken the local housing market, potentially increasing the overall perceived risks. This mechanism can explain our main result, as a decrease in the housing market triggers a reduction in urban land consumption, which, in more aggregate terms, implies a smaller spatial size of the affected cities.

5.2 The Incidence of Land-Use Regulations

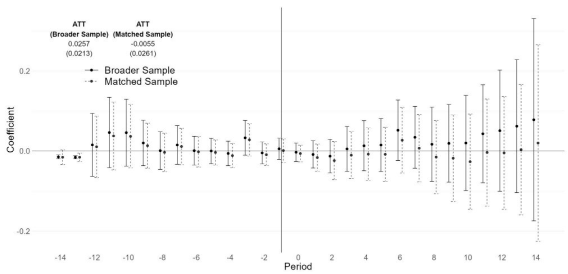
Local governments can respond to natural disasters by adopting new (or stricter) land-use regulations and planning instruments to discourage disorderly urbanization and densification in disaster-prone areas (Burby and Dalton, 1994; Ostriker and Russo, 2022). For example, in landslide-risky areas, the local governments may revise or enact zoning ordinances to enforce lower building height limits, mandate larger minimum lot sizes via land subdivision laws to decrease residential density, or introduce new building codes requiring safer construction standards. These regulations and instruments can be considered adaptive policies with the potential to mitigate the impact of future shocks and bolster the resilience of affected communities.

However, by imposing new regulations or increasing the stringency of existing instruments, development costs rise, putting barriers to urban expansion. If local governments react to disasters this way, this can explain the permanent reduction in urban area size after the landslide exposure documented in Section 4. This hypothesis is also theoretically grounded in the standard monocentric model augmented to include land-use restrictions (Bertaud and Brueckner, 2005). In this setting, when the local government imposes stricter density regulations, developers respond by utilizing more urban land on the city's outskirts, thereby expanding the city's spatial area.

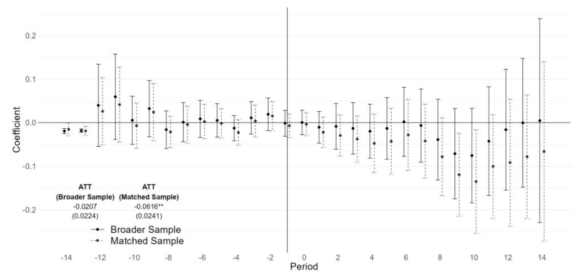
To investigate the role of this mechanism, we examine the impact of landslide exposure on local government's adoption of land-use regulations. Thus, Figure 5 presents the event studies based on equation (2) that show the effect of landslides on the adoption of zoning ordinances (5a), urban growth boundaries (5b), land subdivision regulations (5c), and on building codes (5d). These outcomes are dichotomous variables that assume 1 when the municipality adopts the specific regulation and assume 0, otherwise. Figure 5 shows no evidence that municipalities exposed to landslides increase the adoption of land-use regulations compared to those not exposed. This suggests that this type of adaptive response cannot be an underlying mechanism to explain our main results.

Figure 5: Landslides Effects on Adoption of Land-Use Regulations

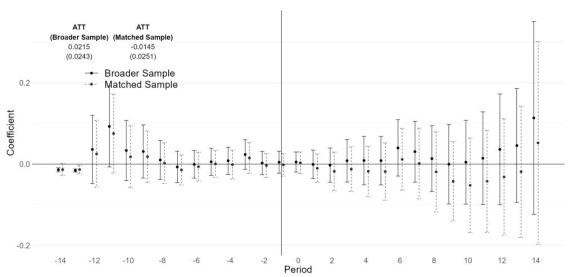
(a) Zoning Ordinances (0/1)



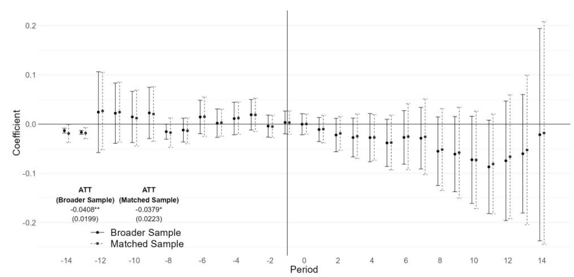
(b) Urban Growth Boundary (0/1)



(c) Land Subdivision Regulation (0/1)



(d) Building Code (0/1)



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figure 5a presents the results for the indicator of zoning adoption, Figure 5b for the indicator of Urban Growth Boundary adoption, Figure 5c for the indicator of land subdivision regulation, and 5d for the indicator of building code adoption. In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

5.3 Changes on Housing Stock Composition

As evidenced in subsection 5.1, the municipalities affected by a landslide experienced a sharp reduction in the stock of housing loans, which suggests a decline in the local housing market. To obtain a more detailed and comprehensive understanding of the effects of landslides on the local housing market, we also estimated the association between landslides and changes in the housing stock using data from the 2000 and 2010 Brazilian Demographic Census. The advantage of the Demographic Census is that it presents detailed information regarding the composition of the housing stock in Brazilian municipalities, differentiating it in several characteristics. The disadvantage is that data is only available for two time periods: 2000 and 2010, which prevents us from using a staggered Difference-in-Differences approach like the previous sections.

Thus, we estimate the association between landslides and housing stock using a 2x2 standard Difference-in-Differences approach with two groups (affected and never-affected) and two time periods (2000 and 2010). We excluded from the analysis all municipalities that experienced landslides after 2010 and used only the matched control group to mitigate the influence of unobservable variables. Table 2 presents the results of this exercise. Initially, we estimated the association between landslides and the log of the total number of housing units (column (1)). Then we separated the housing stock by construction type: single-family units (column (2)) and multi-family units (column (3)).

We also evaluated the composition of housing stock to the quality of infrastructure, adopting the IBGE classification, which categorizes housing into three groups: I) With adequate infrastructure: housing with access to running water, a general sewage network, and garbage collection; II) With inadequate infrastructure (informal settlements): housing without water supply, without bathrooms or drainage connected to a rudimentary septic tank, and without regular garbage collection; III) With semi-adequate infrastructure: housing with at least one inadequate public infrastructure. The results of this analysis are presented in columns (4), (5), and (6) of Table 2. Finally, in columns (7), (8), and (9) of Table 2, we show the results by separating the stock of housing units by size, proxied by the number of bedrooms: small (a single bedroom), medium (two bedrooms), and large (three or more bedrooms).

Table 2: Landslides Effects on Housing Composition

	Log of Housing Stock by Type			Log of Housing Stock by Infrastructure Quality			Log of Housing Stock by Size		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Single-Family	Multi-Family	Adequate	Semi-Adequate	Inadequate	Small	Medium	Big
Landslide	-0.016**	-0.016**	-0.031	-0.222***	-0.042**	-0.057	-0.018	-0.01	-0.0004
	(0.007)	(0.007)	(0.070)	(0.046)	(0.017)	(0.071)	(0.013)	(0.01)	(0.0111)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.998	0.998	0.966	0.965	0.991	0.912	0.995	0.997	0.996
Observations	1,756	1,756	1,756	1,756	1,756	1,756	1,756	1,756	1,756

Note: The table shows the results of estimating the association between landslides and the log of housing stock. Columns (1) to (3) report results by housing type, columns (4) to (6) by infrastructure quality, and columns (7) to (9) by size. Standard errors clustered at the municipality level are in parentheses. Significance levels are denoted as *** p<0.01, ** p<0.05, * p<0.1.

The results in Table 2 show that municipalities affected by landslides experienced a 1.6% reduction in housing stock compared to unaffected municipalities after the disaster. This supports our claim that the decline of the local housing market is one of the main mechanisms linking landslides to the subsequent reduction in the spatial size of cities. Furthermore, this effect is not uniform across different types of housing stock, particularly concerning construction type and infrastructure quality. Specifically, the decline in the housing market in municipalities that experienced landslides was driven by a reduction in the stock of single-family houses (column (2) of Table 2) and housing with adequate infrastructure (column (4) of Table 2). Thus, we can conclude that landslides are not associated with a change in the stock of informal settlements. One possible explanation for the heterogeneity of the effects observed in columns (4) and (6) of Table 2 is that informal housing, being cheaper and easier to reconstruct due to lack of government regulation, tends to suffer less widespread and more transient impacts from disasters.

6 Final Remarks

This paper investigated how landslide shocks affect subsequent urbanization patterns in Brazilian cities. Using a staggered Difference-in-Differences approach that takes advantage of the geography and time variation of landslides across municipalities, we document that cities affected by landslides permanently reduce their urban area size by an average of -6.45% to -8.71% compared to non-affected cities. A greater fragmentation of urban occupation accompanies this reduction. We also show that this result can be explained by the negative income shocks that arise after a landslide and the sharp decrease in the stock of housing loans, suggesting that landslides can increase the overall perceived risk and weaken the local housing markets. Thus, our results suggest that Brazilian cities adapt to landslide shocks through a slowdown in urban land consumption, so these events can be considered a push-down force for urban agglomeration. In this context, this paper contributes to understanding the urbanization dynamics that follow in areas affected by landslides - a type of disaster with a high socioeconomic burden that tends to intensify due to climate change and increasing urban occupation in risk areas.

Preventive and adaptation public policies could be implemented to mitigate the negative consequences of landslides on the local economy and the size of urban agglomerations. The first must be carried out with the main objective of avoiding irregular settlements in disaster-prone areas and encouraging construction in safe locations, which tends to avoid the susceptibility and occurrence of landslides. This can also prevent the shock from propagating to the housing sector, which our results indicate is significantly impacted by landslides. Adaptive policies that increase livability conditions can be implemented to bring more confidence and resilience to affected cities, outweighing the negative effects of landslides, and fostering urban renewal. An important avenue for future research lies in evaluating the efficacy of disaster risk management policies presently in use in Brazil to minimize landslide-induced damages.

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A Variable Descriptions

Table A.1: Summary of Variables, Definitions and Data Sources

Variable	Description	N. Obs.	Source	Frequency
Urban Area Size	The sum of built-up areas in the 1x1km grids that form the municipality.	100,242	Satellite Data MapBiomas	Yearly panel from 2003-2020.
Fragmentation Index	Average proportion of undeveloped land in the different 1x1 km urban grids that compose the municipality.	100,242	Satellite Data MapBiomas	Yearly panel from 2003-2020.
Population	Estimated Population Size in the Municipality	100,242	Population Projections IBGE	Yearly panel from 2003-2020.
GDP per Capita	Gross Domestic Product divided by population size, R$ of 2010.	100,145	GDP Estimatives IBGE	Yearly panel from 2003-2020.
Stock of Housing Loans	Stock of Housing Loans in R$ of 2010.	62,763	ESTBAN Brazilian Central Bank	Yearly panel from 2003-2020.
Dummy of Housing Loans (0/1)	Indicator Variable that assumes 1 when the municipality has a housing loan and zero otherwise.	62,763	ESTBAN Brazilian Central Bank	Yearly panel from 2003-2020.
Dummy of Zoning Ordinance (0/1)	Indicator Variable that assumes 1 when the municipality adopt na zoning policy and zero otherwise.	99,756	MUNIC - IBGE	Yearly panel from 2003-2018.
Dummy of Urban Growth Boundary (0/1)	Indicator Variable that assumes 1 when the municipality adopt na UGB and zero otherwise.	99,288	MUNIC - IBGE	Yearly panel from 2003-2018.
Dummy of Land Subdivision (0/1)	Indicator Variable that assumes 1 when the municipality adopts and a Land Subdivision policy and zero otherwise.	99,756	MUNIC - IBGE	Yearly panel from 2003-2018.
Dummy of Building Code (0/1)	Indicator Variable that assumes 1 when the municipality adopt na Building Code and zero otherwise.	99,630	MUNIC - IBGE	Yearly panel from 2003-2018.
Average Wage	The sum of individual wages in a municipality divided by the number of workers	83,492	RAIS - Brazilian Ministry of Labour	Yearly panel from 2006-2020.
Number of Establishments	Sum of the number of formal establishments in the municipality.	83,492	RAIS - Brazilian Ministry of Labour	Yearly panel from 2006-2020.
Total Employment	Sum of the number of individuals with formal employment in the municipality.	83,492	RAIS - Brazilian Ministry of Labour	Yearly panel from 2006-2020.
Altitude	Average altitude of the municipality in meters.	5,515	IBGE	Cross-Section of 2000
Terrainn Ruggedness Index (TRI)	Average TRI calculated based on Riley, DeGloria, and Elliot (1999)	5,515	QGIS	Cross-Section of 2000
Average Preciptation	Accumulated volume of rain (in mm) per season divided by the corresponding number of days.	5,515	University of East Anglia's Climatic Research Unit	Cross-Section of 2000
Average Temperature	Average temperature (in degrees Celsius) per season.	5,515	University of East Anglia's Climatic Research Unit	Panel of 2000 and 2010
Census Population	Population Size in the Municipality	11,030	Demographic Census IBGE	Panel of 2000 and 2010
Urbanization Rate	Share of the total population that lives in urban areas.	11,030	Demographic Census IBGE	Panel of 2000 and 2010
Share of Informal Settlements	The proportion of houses with inadequate infrastructure to all houses in the municipality.	11,030	Demographic Census IBGE	Panel of 2000 and 2010
Housing Stock by Type of Construction	The number of housing stock separeted by single-family and multi-familiy houses.	11,030	Demographic Census IBGE	Panel of 2000 and 2010
Housing Stock by Infraestructure Quality	The number of housing stock separeted by infraestructure quality: adequated, semi-adequated and inadequated.	11,030	Demographic Census IBGE	Panel of 2000 and 2010
Housing Stock by Size	The number of housing stock separated by size: small (1 bedroom), medium (2 bedroom) and large (3 or more bedrooms).	11,030	Demographic Census IBGE	Panel of 2000 and 2010

B Balance Check Before and After Matching

Table B.1: Comparison of Variables Before and After Matching

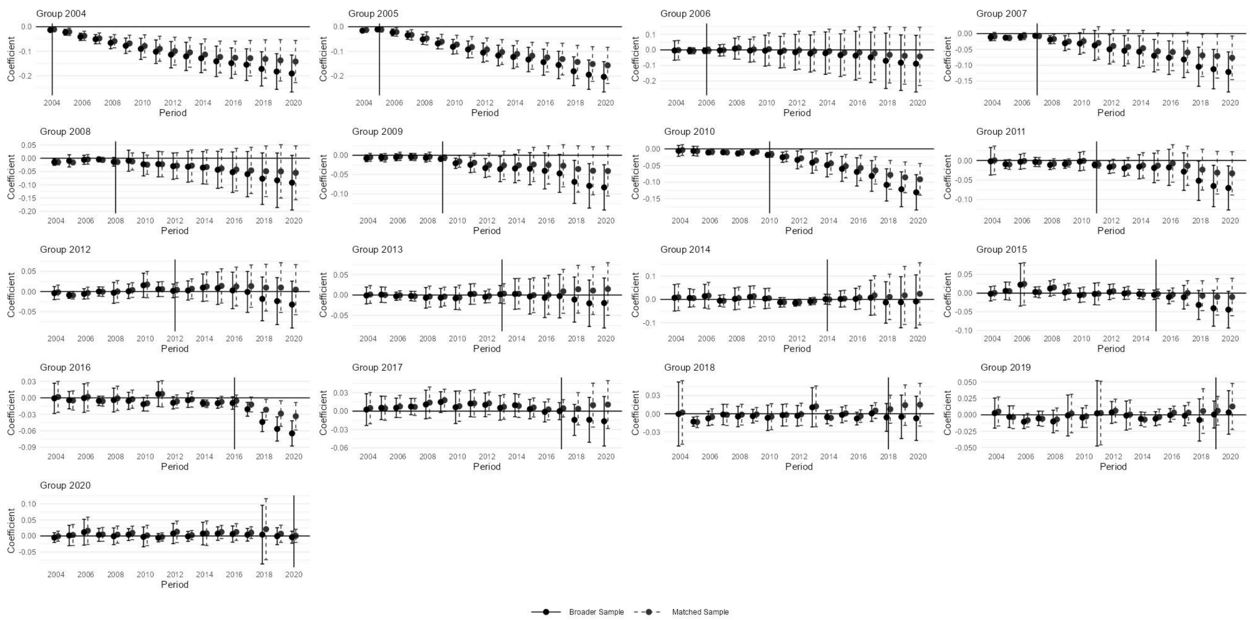
	(1)	(2)	(3)	(4)	(5)
	Treated	Control	Matched Control	Diff (1-2)	Diff (1-3)
Average Altitude	465.14	406.59	483.93	58.55***	-19
	(333.84)	(287.66)	(344.77)	(28.98)	(40.01)
Terrain Ruggedness Index (TRI)	10.82	7.19	10.56	3.63***	0
	(5.01)	(3.98)	(5.09)	(0.43)	(0.59)
Avg. Precipitation (Summer)	182.75	172.47	179.12	10.28***	4
	(49.91)	(70.07)	(55.79)	(4.59)	(6.24)
Avg. Precipitation (Autumn)	84.72	99.32	85.51	-14.6***	-1
	(57.86)	(62.17)	(61.56)	(5.12)	(7.05)
Avg. Precipitation (Winter)	61.54	59.27	63.49	2	-2
	(39.24)	(49.59)	(42.97)	(3.54)	(4.85)
Avg. Precipitation (Spring)	158.38	128.76	158.86	29.62***	0
	(41.2)	(67.77)	(42.07)	(3.91)	(4.91)
Avg. Temperature (Summer)	23.76	24.96	23.74	-1.2***	0
	(1.74)	(1.74)	(1.79)	(0.15)	(0.21)
Avg. Temperature (Winter)	19.10	21.63	19.14	-2.53***	0
	(3.13)	(4.1)	(3.22)	(0.28)	(0.37)
Avg. Temperature (Spring)	22.29	24.34	22.32	-2.05***	0
	(2.27)	(2.7)	(2.24)	(0.2)	(0.27)
Avg. Temperature (Autumn)	20.06	22.09	20.04	-2.03***	0
	(2.89)	(3.64)	(2.97)	(0.26)	(0.35)
Log(Population)	10.25	9.26	9.95	0.99***	0.3***
	(1.45)	(1.02)	(1.2)	(0.12)	(0.16)
Log(GDP Per Capita)	8.43	7.97	8.36	0.46***	0.07*
	(0.69)	(0.7)	(0.68)	(0.06)	(0.08)
Urbanization Rate	0.73	0.57	0.69	0.16***	0.04***
	(0.23)	(0.23)	(0.23)	(0.02)	(0.03)
Share of Informal Settlements	0.06	0.12	0.07	-0.06***	-0.01*
	(0.09)	(0.11)	(0.09)	(0.01)	(0.01)
Log(Urban size)	5.80	4.73	5.46	1.07***	0.34***
	(1.75)	(1.34)	(1.68)	(0.15)	(0.2)
Fragmentation Index	0.79	0.84	0.81	-0.05***	-0.02***
	(0.15)	(0.09)	(0.11)	(0.01)	(0.02)
Region Midwest	0.02	0.09	0.02	-0.07***	0
	(0.14)	(0.29)	(0.14)	(0.01)	(0.02)
Region North	0.05	0.08	0.06	-0.03***	0
	(0.23)	(0.28)	(0.23)	(0.02)	(0.03)
Region Northeast	0.08	0.35	0.09	-0.27***	0
	(0.27)	(0.48)	(0.28)	(0.03)	(0.03)
Region South	0.14	0.22	0.16	-0.08***	0
	(0.35)	(0.42)	(0.37)	(0.03)	(0.04)
Region Southeast	0.71	0.25	0.68	0.46***	0
	(0.46)	(0.44)	(0.47)	(0.04)	(0.05)
N	556	5009	554		

Note: The table displays the mean and standard deviation (in parenthesis) for municipalities separated by treated and control groups. Data are for the baseline year of 2000.

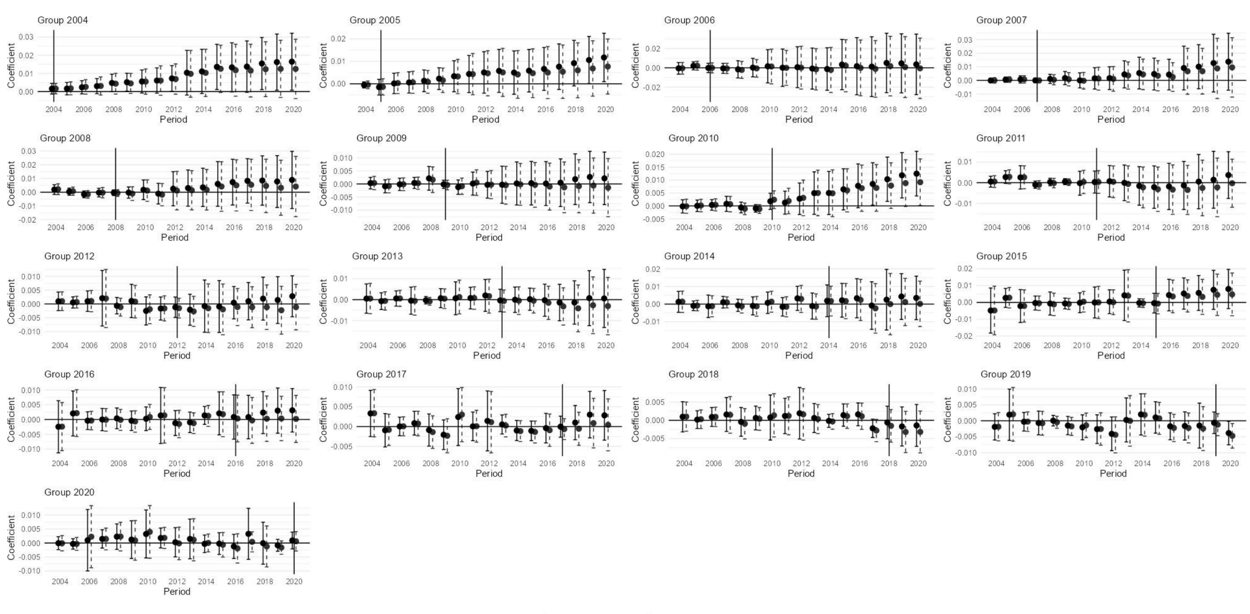
C Heterogeneity by Time of Exposure

Figure C.1: Landslides Effects on Urbanization Patterns: group-specific ATTs

(a) Urban Area Size



(b) Fragmentation Index



Note: These figures show the group-specific ATTs from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level.

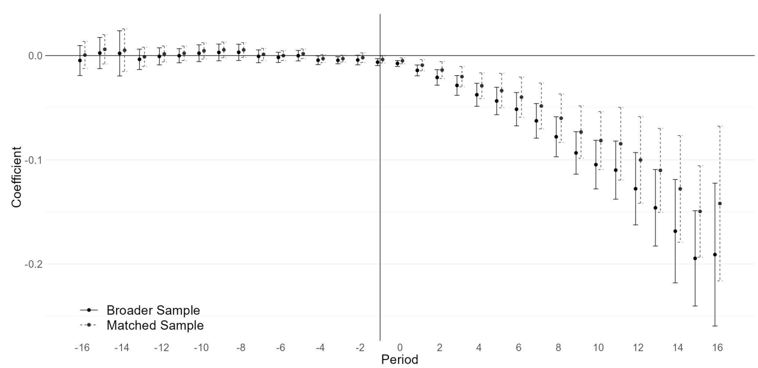
D Robustness Checks

D.1 Control Group based on Not-Yet Treated Units

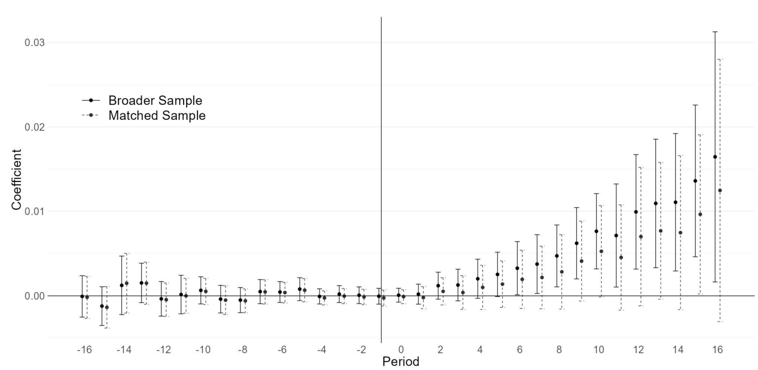
As described in Section 2, our main results are obtained using a control group formed by municipalities that have never been exposed to landslides, both in the broader and matched sample. The Callaway and Sant'Anna (2021) estimator also allows us to build a control group formed by not yet treated units, which is the combination of never-treated municipalities and the ones that have not been treated at a particular point in time but will eventually become treated. Figures D.1a and D.1b present the event studies for the urban area size and fragmentation index using municipalities that have not yet been treated as a control group instead of those that have never been treated. It is observed that our results are not sensitive to this change.

Figure D.1: Robustness Checks I: Not-Yet Treated Units

(a) Urban Area Size - Not-Yet Control Group



(b) Fragmentation Index - Not-Yet Control Group



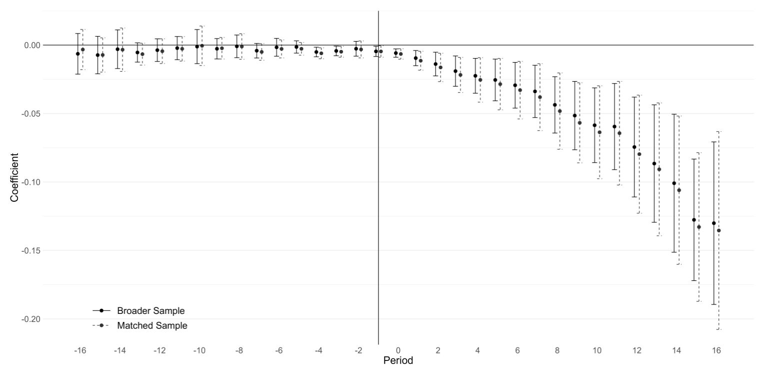
Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level.

D.2 Sample Restricted to the Southeast Municipalities

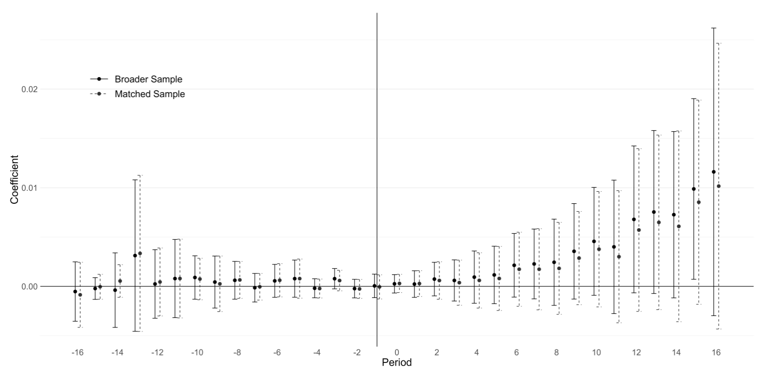
Most landslide events are geographically concentrated in the southeastern region of Brazil. An alternative approach that could generate more similarity between the treatment and control groups is restricting the broad sample to municipalities in the southeast region, as they present greater homogeneity concerning socioeconomic, climatic, and geographical characteristics. Figures D.2a and D.2b present the event studies for the urban area size and fragmentation index restricting the treatment and control group to those in the Southeast region. The results are robust to this restricted sample.

Figure D.2: Robustness Checks II: Southeast Municipalities

(a) Urban Area Size - Southeast Municipalities



(b) Fragmentation Index - Southeast Municipalities



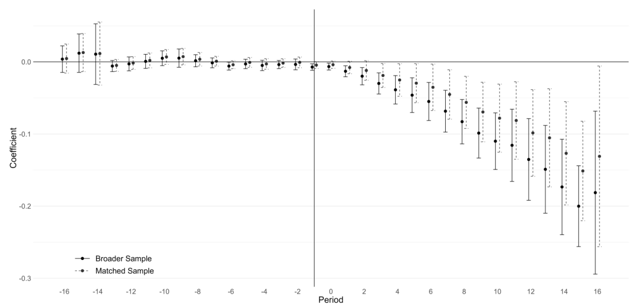
Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figures D.2a and D.2b, present the results for the urban area size and fragmentation index using the broader sample restricted to municipalities in the southeast region.

D.3 Sample Restricted to High-Risk Municipalities

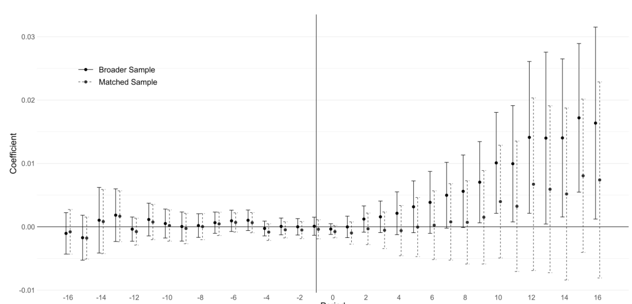
Another way to make the control group more similar to the treatment group without using the matching strategy is to restrict the broad sample to municipalities the government consistently monitors because they have a high risk of suffering future disasters. The *Centro Nacional de Monitoramento e Alertas de Desastres Naturais* (CEMADEN)[13] monitors 959 Brazilian municipalities with a high probability of being affected by natural disasters resulting from mass movements or hydrological processes. The criteria CEMADEN uses to choose this specific group of municipalities is based on the history of past events. The monitoring consists of identifying, mapping, and georeferencing disaster-prone areas. Figures D.3a and D.3b present the event studies for the urban area size and fragmentation index variables, restricting the sample to municipalities effectively monitored by the CEMADEN. It is possible to notice that the pattern of our results practically does not change.

Figure D.3: Robustness Checks III: High-Risk Municipalities

(a) Urban Area Size - High-Risk Municipalities



(b) Fragmentation Index - High-Risk Municipalities



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figures D.2a and D.2b, present the results for the urban area size and fragmentation index using the broader sample restricted to municipalities classified as high-risk by CEMADEN.

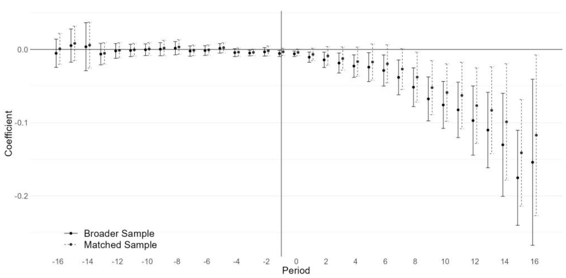
[13] The CEMADEN is a governmental research institute created in 2011 by the Brazilian Federal Government whose objective is to carry out natural disaster management and prevention activities in Brazilian territory.

D.4 The Influence of Other Natural Disasters

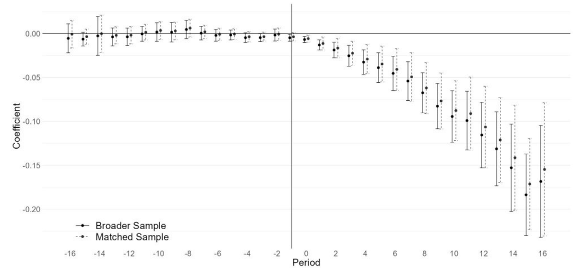
In addition to landslides, Brazil is highly vulnerable to droughts and floods. According to data from Veloso et al. (2022), between 2003 and 2019, 2093 Brazilian cities were affected by droughts and 791 were affected by floods. If these events occur simultaneously with the landslides, our main result may be partially capturing the consequences of these shocks on the urbanization patterns of Brazilian cities rather than the effects of the landslides themselves. Therefore, to investigate whether our result is biased by incorporating municipalities that experienced these alternative disasters, we re-estimate equations (1) and (2) for the broad sample and the matched sample by dropping the set of municipalities that experienced flood (Figures D.4a and D.4c) and municipalities that experienced droughts (Figure D.4b and D.4d). Although the confidence intervals become more imprecise, the general effect of landslides on the urban area size and the fragmentation index remains unchanged.

Figure D.4: Robustness Check IV: The Influence of Other Natural Disasters

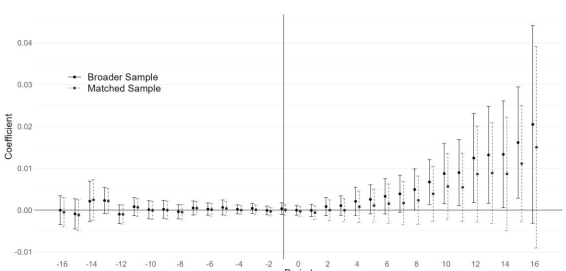
(a) Urban Area Size - Dropping Flooded Cities



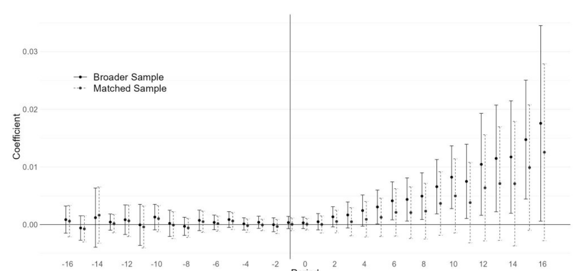
(b) Urban Area Size - Dropping Cities with Drought



(c) Fragmentation Index - Dropping Flooded Cities



(d) Fragmentation Index - Dropping Cities with Drought



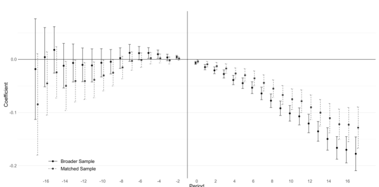
Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figures D.4a and D.4b show the results for urban area size droping municipalities that experienced flood or drought, respectively. Figures D.4c and D.4d show equivalent results for the fragmentation index. In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

D.5 Alternative DiD-Robust Estimators

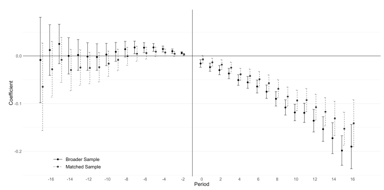
As discussed in Section 2, we utilize the DiD-robust estimator developed by Callaway and Sant'Anna (2021) because we believe it adapts well to our research context, as the effects of landslides tend to vary in time and during the exposure period and the shocks have a staggered nature. Despite this, as pointed out by Roth et al. (2023), the choice of the best DiD-Robust estimator is trickier, involving some trade-offs between efficiency and the strength of the parallel trend assumption necessary for identification. To check whether our results are robust to alternative Difference-in-Differences estimators, we also estimate the event study using the standard TWFE estimator, the Borusyak, Jaravel and Spiess (2021) estimator, and the Gardner (2022) estimator. The results are presented in Figure D.5. Although slight pre-trends are observed in some cases, the negative and permanent impact of landslides on the urban area size and the positive and lasting impact on urban fragmentation are maintained.

Figure D.5: Robustness Checks V: Alternative DiD Estimators

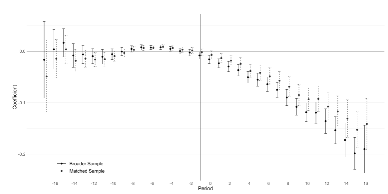
(a) Urban Area Size - TWFE



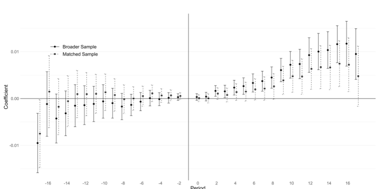
(b) Urban Area Size - Borusyak, Jaravel and Spiess (2021) Estimator



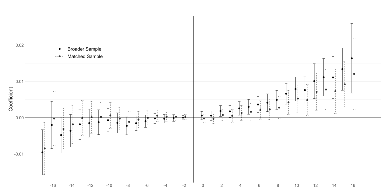
(c) Urban Area Size - Gardner (2022) Estimator



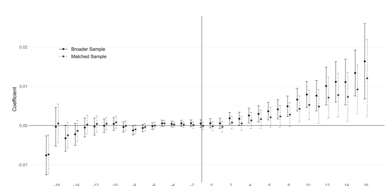
(d) Fragmentation Index - TWFE



(e) Fragmentation Index - Borusyak, Jaravel and Spiess (2021) Estimator



(f) Fragmentation Index - Gardner (2022) Estimator



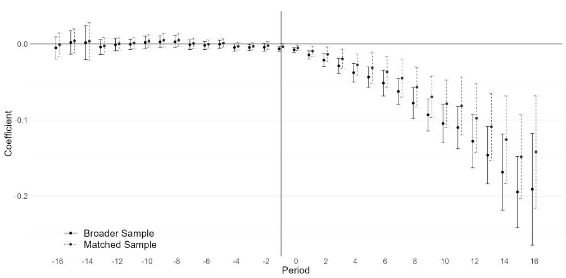
Note: These figures show the event study plots using the following estimators: TWFE (figures D.5a and D.5d), the DiD-Robust estimator from Borusyak, Jaravel and Spiess (2021) (figures D.5b and D.5e) and the DiD-Robust estimator from Gardner (2022) (figures D.5c and D.5f). We report 95% confidence intervals with standard errors clustered at the municipality level. In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

D.6 Alternative Inference Procedures

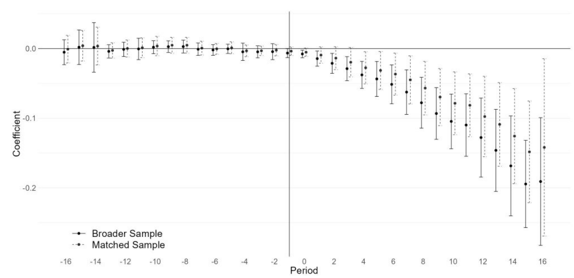
In our main result, we adopt the standard inference practice and clustered the standard errors at the municipality level, as this is the geographic unit that receives the treatment (MacKinnon, Ørregaard Nielsen and Webb, 2022). To investigate whether our result is driven by this choice, we also estimated equation (2) using standard errors robust to heteroskedasticity without any cluster (Figures D.6a and D.6c) and standard errors clustered at the microregion level (Figure D.6b and D.6d), which is a more aggregated geographic unit composed of groups of municipalities with similar socioeconomic characteristics. It is noted that our results are quite robust to different inference procedures.

Figure D.6: Robustness Check VI: Alternative Inference Procedures

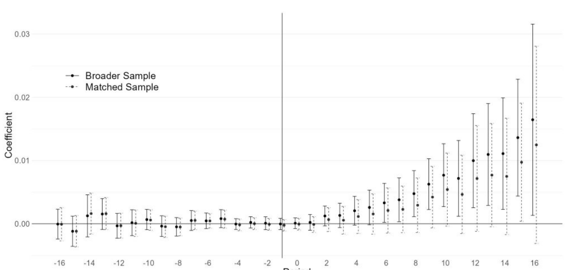
(a) Urban Area Size - Heteroskedasticity Robust SEs



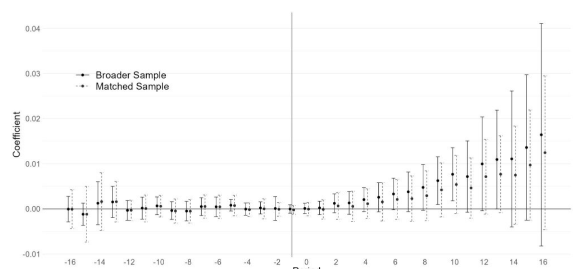
(b) Urban Area Size - SEs Clustered at Microrregion Level



(c) Fragmentation Index - Heteroskedasticity Robust SEs



(d) Fragmentation Index - SEs Clustered at Microrregion Level



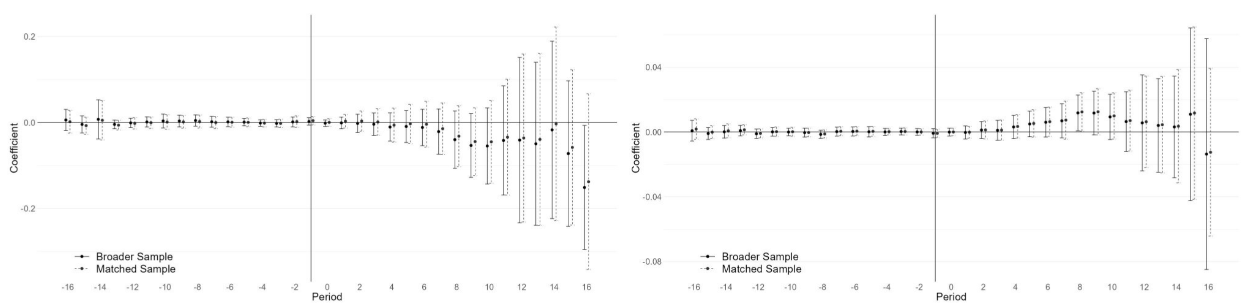
Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with heteroskedasticity robust standard erros (figures D.6a and D.6c) and standard errors clustered at the microrregion level (figures D.6b and D.6d). In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).

D.7 Spatial Spillovers of Landslides

The negative effects of landslides in affected municipalities can spread to neighboring municipalities for several reasons. Firstly, a potential negative income shock associated with a natural disaster tends to propagate across broader geographic areas (Lima and Barbosa, 2019) as a consequence of input-output connections, trade flows, and the interregional mobility of factors of production. Furthermore, if landslides stimulate out-migration, neighboring municipalities may mainly absorb this flow, affecting their urbanization path. In these situations, there would be a violation of the stable unit treatment value assumption (SUTVA), which establishes that the treatment status of a unit does not affect the outcomes of different units (Delgado and Florax, 2015). If SUTVA is violated, our main estimates become biased. To evaluate the spatial spillover of landslides and the plausibility of SUTVA in our context, we estimated equations (1) and (2) by comparing the subgroup of municipalities *indirectly* affected by the landslides (defined as those that are not affected but share a border with those affected) with the rest of the not affected ones. This approach drops the municipalities that directly experienced landslides from the analysis. If there is any significant effect, this indicates that municipalities not affected by landslides that are geographically close to those affected also change their urbanization patterns in response to disasters, suggesting that spatial spillovers are relevant. Figure D.7 presents the results of the indirect effects of landslides for the urban area size (Figure D.7a) and for the fragmentation index (Figure D.7b). It is possible to note that landslides do not generate economically relevant spillovers, which suggests that there is no violation of SUTVA in our setting.

Figure D.7: Robustness Check VII: The Spatial Spillovers of Landslides

(a) Urban Area Size (b) Fragmentation Index



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. In this estimation, we compared the evolution of urbanization patterns in the indirectly affected municipalities (which belong to the never-affected group but border those affected) with the evolution of urbanization patterns of the other never-affected municipalities. We report 95% confidence intervals with standard errors clustered at the municipality level.

D.8 Summary of Robustness Checks

Table D.1: Comparison between post-treatment ATTs

	Log Urban Size		Fragmentation Index	
	(1)	(2)	(3)	(4)
	Broader Sample	Matched Sample	Broader Sample	Matched Sample
Baseline Estimation				
ATT	-0.0871***	-0.0645***	0.006***	0.0041***
	(0.0066)	(0.0087)	(0.0012)	(0.0015)
N Treated Units	505	503	505	503
N Control Units	5013	554	5013	554
N Observations	99324	19026	99144	19026
Not Yet Treated as a Control Group				
ATT	-0.0871***	-0.0664***	0.006***	0.004***
	(0.0069)	(0.0082)	(0.0012)	(0.0014)
N Treated Units	505	503	505	503
N Control Units	5013	554	5013	554
N Observations	99324	19026	99144	19026
Sample considering only Southeast				
ATT	-0.0525***	-0.0564***	0.0039***	0.0032**
	(0.0075)	(0.0091)	(0.0014)	(0.0016)
N Treated Units	346	344	346	344
N Control Units	1275	375	1275	375
N Observations	29178	12942	29178	12942
Sample of High-Risk Municipalities				
ATT	-0.0896***	-0.0633***	0.0073***	0.0024
	(0.0109)	(0.013)	(0.0019)	(0.0023)
N Treated Units	243	242	243	242
N Control Units	691	148	691	148
N Observations	16794	7020	16758	7020
Removing Flooded Municipalities				
ATT	-0.0651***	-0.0494***	0.007***	0.0044**
	(0.0094)	(0.0118)	(0.0018)	(0.0021)
N Treated Units	303	301	303	301
N Control Units	4387	415	4387	415
N Observations	84420	12888	84240	12888
Removing Drought Municipalities				
ATT	-0.0782***	-0.0719***	0.0065***	0.0038**
	(0.0074)	(0.0099)	(0.0014)	(0.0017)
N Treated Units	357	356	357	356
N Control Units	2087	355	2087	355
N Observations	43992	12798	43938	12798
TWFE Estimator				
ATT	-0.0629***	-0.0872***	0.0036***	0.0058***
	(0.0093)	(0.0072)	(0.0016)	(0.0014)
N Treated Units	505	503	505	503
N Control Units	5013	554	5013	554
N Observations	99324	19026	99324	19026
Borusyak, Jaravel and Spiess (2021) Estimator				
ATT	-0.0629***	-0.0872***	0.0036***	0.0058***
	(0.0093)	(0.0072)	(0.0016)	(0.0014)
N Treated Units	505	503	505	503
N Control Units	5013	554	5013	554
N Observations	99324	19026	99324	19026
Gardner (2022) Estimator				
ATT	-0.0729***	-0.0963***	0.004***	0.0063***
	(0.0111)	(0.0097)	(0.0019)	(0.0017)
N Treated Units	505	503	505	503
N Control Units	5013	554	5013	554
N Observations	99324	19026	99324	19026
Spatial Spillovers of Landslides				
ATT	-0.0342	-0.0264	0.0043	0.0047
	(0.0238)	(0.0245)	(0.0049)	(0.0053)
N Treated Units	97	97	97	97
N Control Units	3747	205	3747	205
N Observations	69192	5436	69048	5436

Notes: The table presents the post-treatment ATT estimates for different samples. Standard errors are in parentheses. Significance: *** represents $p < 0.01$, ** represents $p < 0.05$, * represents $p < 0.1$.

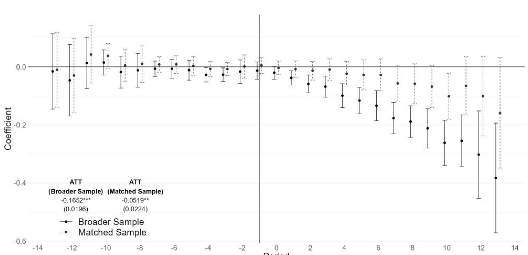
E Additional Mechanisms

E.1 The Effect on Wages, Employment and Establishments

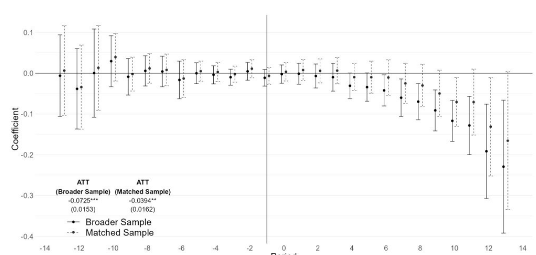
To have a better idea of the effects of landslides on the economic activity of the exposed municipalities, we also investigated the impacts of landslides on the following variables: average wages, number of employees, and number of establishments. These variables were extracted at the municipal-year level from the *Relação Anual de Informações Sociais* (RAIS), a database constructed by the Brazilian Ministry of Labor that is collected annually and that considers the entire universe of the formal labor market in Brazil. Figure E.1 presents the results of the impact of landslides on these variables using our staggered Difference-in-Differences estimator. In general, it is possible to note that landslides can be considered a negative income shock since the exposed municipalities face reductions in the average wage (post-treatment ATT of -5.19% to -16.5%), a reduction in employment (post-treatment ATT of -3.93% to -7.23%), and a reduction in the number of establishments (Post-Treatment ATT of -4.94% to -6.35%).

Figure E.1: Landslides Effects on Average Wage, Average Employment and Number of Establishments

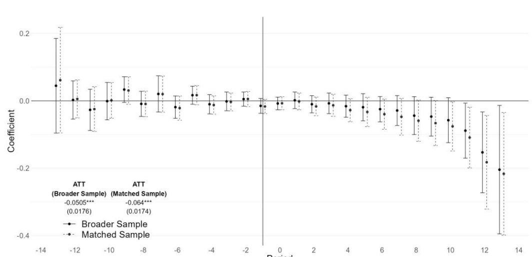
(a) Log of Average Wage



(b) Log of Employment



(c) Log of Number of Estabilshments



Note: These figures show the event study plots from the Callaway and Sant'Anna (2021) estimator. We report 95% confidence intervals with standard errors clustered at the municipality level. Figure E.1a presents the results for the log of Average Wage, Figure E.1b for the log of Employment and Figure E.1c for the log of the number of establishments. In each figure, we present two specifications: one that considers all never-affected municipalities as a control group (Broader Sample) and another that considers a subgroup of matched municipalities as a control group (Matched Sample).