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To Burn a Slum:
Urban Land Conflicts and the Use of Arson against *Favelas*

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WORKING PAPER SERIES Nº 2024-13

DEPARTMENT OF ECONOMICS, FEA-USP
WORKING PAPER Nº 2024-13

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This paper investigates the understudied phenomenon of urban land conflicts in contexts with weak enforcement of property rights. I examine, both theoretically and empirically, the use of arson as a violent tool to force slum removal from high-value land in cities. Leveraging fine-grained geocoded data, I employ panel regression and Difference-in-Differences analyses to demonstrate that the probability of slum fires dramatically increases with rising land prices. This effect is nonlinear and driven exclusively by slums situated on private lands, highlighting the role of high-powered incentives behind arson. These results illustrate how urban land conflicts can have different outcomes than their rural counterparts.

Keywords: Urban Land Conflict, Slums, Arson, Violence, Property Rights

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April, 2024

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This paper investigates the understudied phenomenon of urban land conflicts in contexts with weak enforcement of property rights. I examine, both theoretically and empirically, the use of arson as a violent tool to force slum removal from high-value land in cities. Leveraging fine-grained geocoded data, I employ panel regression and Difference-in-Differences analyses to demonstrate that the probability of slum fires dramatically increases with rising land prices. This effect is nonlinear and driven exclusively by slums situated on private lands, highlighting the role of high-powered incentives behind arson. These results illustrate how urban land conflicts can have different outcomes than their rural counterparts.

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[*]I thank Sergio Firpo, Fernando Ferreira, Rodrigo Soares, Eduardo Faingold, Mariaflavia Harari, Maisy Wong, Bruno Barsanetti, Paulo Furquim, and Leila Pereira, as well as all seminar and conference participants at Insper, Wharton, the 2018 Ronald Coase Institute Workshop, the 2019 Urban Economics Association Summer School at LSE, the 44th EBE-SBE, the Paris School of Economics Workshop on Neighborhoods and Local Interactions, and the 2023 LACEA-LAMES for their extremely valuable comments and suggestions. I also thank the São Paulo State Research Foundation (FAPESP) for their financial support (scholarship processes 2018/14183-3, 2019/02389-9, 2023/11134-0).

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1 Introduction

A growing body of evidence in Economics shows that weak enforcement of land property rights can lead to violence (Alston et al., 2000; Fetzer and Marden, 2017). When formal institutions fail to provide legal solutions, squatters and landowners often fight to gain control of contested land. While extensive attention has been devoted to understanding this phenomenon in rural areas, little is known regarding the emergence of violent land conflicts in urban settings (Lombard and Rakodi, 2016). Such conflicts are likely to arise in many cities, where landowners and slum residents compete for valuable land, but local governments often lack the capacity or motivation to resolve these disputes (Brueckner and Selod, 2009; Jimenez, 1985; Lanjouw and Levy, 2002; Holston, 1991). This is expected even when slum-occupied land is private and property rights should be better enforced.[1]

This paper provides novel evidence on whether and how urban land conflicts become violent. I investigate both theoretically and empirically the use of arson as one potential strategy in urban land conflicts — a possibility suggested in many settings. In the US, there were famous cases of arson associated with gentrification and displacement reported in Hoboken (NJ), Boston (MA), and other urban centers in the 1980's (Gottlieb, 2019; Brady, 1983).[2] The wave of what became known as *arson-for-profit* was even discussed in legislative hearings in the US Congress (U.S. Congress, 1980). In developing countries, where the enforcement of land property rights tends to be weak, arson is allegedly used to destroy slums in premium neighborhoods, force residents out, and clear the land for sale or development (Ockey, 1997; Rahman, 2001; D'Andrea, 2012; Barcelos and Viana, 2017; Malhotra, 2018). For urban landowners, using this strategy could be more advantageous than engaging in overt armed confrontation, which is typically the case in rural land conflicts. Because fires in slums spread fast, it is hard to determine their true causes, let alone find potential arsonists (Braga and Landim, 2008; Walls et al., 2017). Therefore, landowners could use arson to enforce their claim over contested land while still evading the high-monitoring environment of dense urban areas.

To examine the use of arson, I explore how the incentives for engaging in violent land conflict vary according to prices and legal ownership (private or public) of slum land. I design an optimal stopping model of arsonist decision-making and derive testable

[1] Contestability of private land can arise, for example, when there is room for adverse possession, i.e., when legislation allows for squatters to become legal owners of the squatted land if they meet some criteria (Handzic, 2010; Baker et al., 2001).

[2] In Hoboken, for instance, rent control in a rapidly gentrifying area drove strong incentives for landlords to displace tenants, renovate units, and rent at a higher price afterwards.

implications relating arson to land value and ownership. On the one hand, higher land value drives higher willingness to remove slums (Jimenez, 1985; Turnbull, 2008; Brueckner and Selod, 2009; Brueckner et al., 2019). On the other hand, private owners should be more willing to remove slums than public ones. While the former make an individual decision, the latter face a collective action problem that lowers incentives to remove slums (Olson, 1971).

To test these implications, I construct a unique database spanning from 2001 to 2016, incorporating geocoded information on slums, fires, and land prices in São Paulo, one of the world's largest cities (United Nations, 2018). This comprehensive dataset allows me to explore variation in both land value and ownership across slums and over time. I examine how these factors affect the prevalence of arson against slums using both cross-sectional and difference-in-differences analyses.

São Paulo provides an interesting, albeit not isolated,[3] case due to its large number of slums and numerous reports of fires connected to slum clearance.[4] These events gained such proportion that an inquiry commission was instituted by the city council. Although hard proof of wrongdoings is scarce, suggestive evidence indicates that a large share of slum fires in the city have been caused by arson (Bruno, 2010).[5] Moreover, the city has slums in both private and public lands spread across several different neighborhoods with varying land prices.

The main hypotheses to be tested come from a dynamic framework inspired by the classical model of real estate development in Capozza and Sick (1994). In my context, I show that landowners decide to burn slums depending on whether land value is above or below a given threshold. If it is above, then it is profitable for the landowner to immediately burn the slum and develop the plot instead of waiting for legal institutions to remove the slum. Otherwise, it is better to wait for a legal solution. This framework predicts a relationship between arson and land value that is not only positive, but also non-linear. In other words, the probability of arson should increase discontinuously when land prices are high enough.

Such behavior should be mostly driven by private landowners because they can retain all the value from removing the slum. If the land is public, however, arson faces additional detracting factors that are absent in private lands. First, from the perspective of local governments, fires can be costly, since municipalities might be required to aid the

[3] Similar reports of arson being used against slums have been found for Bangladesh, India, and Thailand (Mahmud, 2016; Rahman, 2001; Malhotra, 2018; Ockey, 1997).

[4] For a more complete documentation of episodes covered in media articles, please refer to the Appendix.

[5] Bruno (2010) shows that 30% of slum fires in São Paulo in the beginning of the 2000's were caused by arson, although there is no data on the motivation behind these cases.

victims. Second, people typically blame authorities for not preventing fires, which can hurt electoral outcomes. Finally, from the perspective of neighbors who own properties around slums, clearing the land could potentially bring positive externalities. However, this is counterbalanced by a collective action problem, since the cost of arson falls to one or few individuals (Olson, 1971).

I design two empirical exercises to investigate these theoretical results. In both cases, the main challenge arises from not observing arson directly, but rather slum fires in general. This type of measurement error can lead to omitted variable bias if slums with higher land value are also closer to jobs and amenities, drawing more residents and being subject to more domestic accidents involving fire, for instance.

First, I explore cross-sectional variation in slum land value to test whether the probability of arson increases in a non-linear fashion. I run a linear probability model to compare the yearly incidence of fire for slums in different quantiles of land value and across private and public lands. To mitigate potential omitted variable bias arising from measurement error, I rely on multiple features of both the empirical model and the setting: (i) several controls for observable characteristics that are both affected by land value and affect fire hazard, such as slum density and infrastructure; (ii) district-specific year trends to estimate very local differences in probability of arson within the city; (iii) the fact that slums were built decades prior to the current dynamics of land prices, which should limit sorting; (iv) the interaction of land value with private/public land ownership is exogenous to the probability of fire.

Overall, I find that the probability of fire is substantially higher when slum land is more expensive. This effect is entirely driven by slums in the highest quantiles of the land value distribution, which is consistent with the non-linearity predicted by the model. Moreover, I only observe a significant effect for slums that occupy private land. For slums in public lands, there is no evidence of strategic arson.

I also provide further robustness to these findings by running a Difference-in-Differences model to estimate the relationship between land value and strategic arson across private and public lands. I leverage a plausibly exogenous shock in land value caused by a large urban intervention intended to renovate a specific area of the city. In 2004, the municipal government of São Paulo started auctioning permits that allowed developers to build above zoning restrictions inside the intervention area. With funds raised from such auctions, the government invested heavily in urban infrastructure in that same area. This attracted many developers, causing demand for land to increase rapidly, as well as land value.

I take advantage of the fact that many slums existed in the region, but some were inside the intervention zone whereas others were not. I categorize slums inside the intervention area as more exposed to the shock than those outside of it. Then, I compare the evolution of slum fires in both groups before and after the intervention. If strategic arson is happening, one should expect an increase in the probability of fire for more exposed slums, i.e., those inside the intervention area. Moreover, as in the cross-sectional analysis, this effect should be driven mainly by slums in private lands.

Although this Difference-in-Differences yields a more local effect, it also gives a more precise estimate compared with the cross-sectional approach. I find that the probability of fire does increase substantially in slums more exposed to the shock in land value. Results are robust to the inclusion of several controls, slum and year fixed effects, and different restrictions in sample period and size. Moreover, as before, results are only positive and significant for slums in private lands, whereas null for those in public lands. Finally, the magnitude of results from both empirical approaches seem to be in line. The shock provided by the intervention for exposed slums is sufficient to move them across the theoretical land value threshold that makes strategic arson profitable, which was estimated in the cross-sectional model. Therefore, local estimates produced by the Difference-in-Differences are consistent with the non-linearity suggested by the city-wide, cross-sectional results.

With two alternative empirical exercises pointing to the same conclusions, this paper provides evidence that arson might be a violent instrument used in urban land conflicts. These findings contribute to the growing literature about land conflicts and weak enforcement of property rights (Alston et al., 2000, 2012; Fetzer and Marden, 2017). Here, I document that urban land conflicts can also become violent, but the outcome is different from what we observe in rural or remote areas of developing countries.

Additionally, I contribute to a fundamentally theoretical literature about slum removal. Using fine-grained information on slums, this paper provides a within-city empirical test of the relationship between land value and attempts of eviction (Jimenez, 1985; Turnbull, 2008; Brueckner and Selod, 2009; Shah, 2014; Brueckner et al., 2019). Moreover, I show both theoretically and empirically that such relationship is likely non-linear due to the dynamic nature of real estate development.

Finally, this paper is more closely related to Henderson et al. (2020). These authors develop a general equilibrium model to study the transition of neighborhoods from slum to non-slum status. Although we both use a similar type of optimal stopping framework, they are more interested in explaining city growth and how this interacts with informal property rights in slums. In my case, I am focused on land conflicts that arise before the transition can happen and on how they may become violent. This paper adds to their conclusions by showing that slum residents face extra — and potentially invisible — costs when the formal city expands towards their neighborhoods.

The remainder of the paper is organized as follows. Section 2 describes institutional factors behind strategic arson in slums. Section 3 then provides a theoretical framework to help both understand this phenomenon and guide the empirical analysis. Section 4 presents the data, and Sections 5 and 6 show the main results of the paper using cross-sectional and Difference-in-Differences analyses, respectively. Section 7 concludes.

2 Slum Removal and Fires in São Paulo

Land conflict is quite common in Brazil and is frequently associated with weak enforcement of property rights (Alston et al., 2000, 2012; Fetzer and Marden, 2017; Chiavari et al., 2021). The latter can arise not only because the government lacks capacity to resolve disputes, but also due to rather convolute rules allowing for adverse possession.[6] Although designed to promote land reform, this legal instrument can create judicial uncertainty and promote disputes rather than avoid them. (Holston, 1991; Gonçalves, 2009)

In Brazilian cities, lack of land property rights is typically present in slums, which were home to 31% and 15% of the country's urban population in 2000 and 2018, respectively (UN-Habitat, 2020). In São Paulo, the largest city in the Southern Hemisphere (Schneider et al., 2022), rapid urbanization during the second half of the twentieth century was driven by strong migration from rural areas. These migrants were met with increasingly more restrictive zoning codes, which partially forced them to settle and build their own houses in peripheral areas of the city (Rolnik, 1995). In 2000, São Paulo had approximately 10% of its inhabitants living in slums, amounting to more than one million people (Pasternak, 2006).

For slum residents, having no land property rights can have real effects, such as worse labor market outcomes (Field, 2007) and lower housing investments (Galiani and Schargrodsky, 2010). Moreover, they face constant threat of being displaced by a slum removal — and periodically have to face one. In this case, their houses are destroyed, they have to move elsewhere, and they do not necessarily get any government aid to find a new place. According to data from Observatório das Remoções (2022), which combines both self-reported and official information, more than half of all slums in São Paulo were either

[6] This was established by Article 182 of the Federal Constitution (Civil, 1988) and it is also regulated in Federal Laws 6.969/81 and 10.406/02 (Brasil, 1981, 2002)

removed or under threat of removal during the 2017-2022 period.

Nevertheless, although threat of removal is prevalent, it is not necessarily true that removing slums is straightforward. In São Paulo, again according to Observatório das Remoções (2022), only 15% of slums under threat of removal have actually been removed either completely or partially between 2017 and 2022. This gap between potential and actual evictions can have multiple explanations. On the one hand, slum residents might resist eviction, especially if they can claim adverse possession or if the removal would bear large political costs. On the other hand, court decisions and appeals can take many years, even in the absence of adverse possession.[7] In either case, this low rate of removals may become a problem from the perspective of *de jure*[8] landowners who decide to pursue the eviction of slum residents from their lands.

Economic theory suggests that landowners are more willing to seek slum removal if the value of slum-occupied land is higher. For landowners, increasing land prices mean that alternative uses for that land — such as developing an apartment building and renting the units — are more profitable than allowing the slum to remain there, with residents paying no rent at all (Brueckner and Selod, 2009; Henderson et al., 2020). Empirically, there is some evidence that higher housing prices caused by urban renovations led to the removal of slums in India Gechter and Tsivanidis (2018).

As suggested before, however, slum removal is not guaranteed. Some owners of slum-occupied land face increasing prices, but are unable to remove the slum and profit from this situation. This creates a conflict between landowners and slum residents that, if left unresolved by authorities, can escalate to violence (Lombard and Rakodi, 2016). This is what happens in rural areas, where landowners and squatters arm themselves and fight for land (Alston et al., 2000; Fetzer and Marden, 2017).

In cities, violence need not happen in the same way, especially because government monitoring is stronger in these areas. Instead of overt armed confrontation, many pieces of anecdotal evidence suggest that slum fires are one potential outcome of land conflict (D'Andrea, 2012; Ockey, 1997; Rahman, 2001).[9] The reason is that fires can effectively des-

[7] Among repossession lawsuits for formal houses in the city of São Paulo, which are supposed to be simpler than those involving slums, 25% take more than 2 years to be ruled and some even last up to 9 years.

[8] *De jure* landowners have legal ownership over the land. This is constrasted with *de facto* owners, who typically possess a land by occupying it. The latter would be the case of slum residents. A more detailed explanation about *de jure* and *de facto* ownership and its relationship with land conflicts is provided in (Alston et al., 2012).

[9] Even in the US, arson has been suggested as being used in urban land conflicts. Gottlieb (2019) studies how the series of fires in Hoboken (NJ) were associated with landlords' attempts to displace tenants from a gentrifying zone.

troy slums and clear the land for alternative use, while still leaving little trace of wrongdoing. Still understudied, this hypothesis is not new. In Brazil, one of the oldest references to this possibility dates back to 1969, when a slum in Rio de Janeiro called *Favela do Pinto* was destroyed by a suspicious fire. At the time, residents tried to resist removal driven by urban renovations, but the fire forced them to displace (Brum, 2011). More recently, several news pieces present a similar story for São Paulo and other cities, suggesting many slum fires in high-value neighborhoods were not accidents, but instead motivated by landowners' willingness to remove those slums.[10] This is what I call *strategic arson*.

Even though circumstances seem very convenient for landowners, finding the true causes behind these fires can be challenging for authorities. This is partly because slums are built out of very combustible materials that make fires spread quickly, which hinders attempts to trace back their origin (Braga and Landim, 2008; Walls et al., 2017). Still, there is evidence that 30% of slum fires in São Paulo are caused by arson, strategic or not (Bruno, 2010). Moreover, there seems to be a high correlation between fires and slum removal. Based on a sample of 86 validated observations[11] from Observatório das Remoções (2022), 60% of slums removed in São Paulo between 2001 and 2016 had a fire episode in that same period. Furthermore, the probability of slum removal in any given year is seven times higher if that slum suffered a fire in the same year or in the previous one.

Legal ownership of slum-occupied land is another important feature to consider when studying removals and strategic arson. Land prices can have heterogeneous effects on conflict depending on whether slums are in private or public land. When the land is private, landowners retain the full value of removal. After clearing the slum, private owners can either sell or develop their property and profit from this — as suggested in theoretical models (Jimenez, 1985; Hoy and Jimenez, 1991; Brueckner and Selod, 2009; Selod and Tobin, 2018). In this case, choosing whether to remove a slum or not is a matter of comparing the benefit of using the land for something else against the cost of either legally or illegally pursue the removal. In the end, higher land value should lead to a higher probability of removal.

Alternatively, when slums are in public land, either people who own formal properties nearby or the government itself might be interested in slum removal (Shah, 2014). In the former case, neighbors living around a slum might be willing to petition the eviction for the government if they believe this would increase property value in the neigh-

[10] Appendix B provides some pieces of news about suspicious slum fires that could have been caused by economic motivation.

[11] Based on Google Earth imagery, I validated which removals reported by Observatório das Remoções (2022) actually happened. I only considered a slum as removed if its buildings were visibly destroyed.

borhood. There is, however, a collective action problem, because neighbors would need to coordinate effort (Olson, 1971). If some value the removal less than others, the equilibrium might be such that the local government is not sufficiently pressured to evict slum residents.

The government itself could also be interested in removing slums, but it is less clear how it could benefit from the removal. Money from selling the land is not necessarily going to mayors and their allies. Moreover, there might be a political cost for those in power, because news portraying the struggle of evicted slum residents typically put local governments under pressure for providing aid. Finally, local regulations sometimes mandate that the government helps displaced slum residents.

There is also some suggestive evidence of differing incentives for removing slums in private or public lands. Based on data from Observatório das Remoções (2022), the probability of evicting slums in private land is twice as high as that of evicting slums in public land.

To provide a more formal discussion about the role of land value and ownership in strategic arson, I lay out the main features of a theoretical model in the next section. Although the way land value affects arson might seem straightforward, the model still provides an important — and perhaps less obvious — insight about the non-linearity of such effect.

3 Conceptual framework

In this section, I design an optimal stopping framework to model landowners' decision to whether burn slums or wait for a court-mandated eviction. This is somewhat analogous to Henderson et al. (2020), although in their case they are interested in slum replacement without violent conflict. This approach has also been used before to explain landowners' decision to develop empty land plots (Capozza and Li, 1994; Capozza and Sick, 1994) based on housing prices.

In the canonical case, the landowner compares the potential gains of developing a land plot with those of an outside option, which is typically a constant agricultural income. As housing gets more expensive, developing an empty land plot becomes increasingly more attractive. Eventually, prices hit a threshold beyond which it is unequivocally more profitable to develop the plot. When this happens, the landowner irreversibly decides to convert the land plot into a building.

In this paper, the decision to whether develop a land plot or not is also present, but first the landowner is confronted with the fact that the plot is occupied by a slum instead of empty. To deal with this, she can either wait for a legal removal or burn the slum to force residents out. As in the canonical case, in every period of time t the agent faces a trade-off between *waiting* for another period or taking irreversible action to interrupt the slum occupation violently. Behind this decision is the value of the slum-occupied land p_t, which determines the landowner's utility, $u(p_t)$, in case of slum removal.

Price p_t can be more or less relevant depending on whether slum-occupied land is private or public. If it is private, p_t impacts directly what the landowner gains from the eviction, by either developing or selling the plot. In the case of public lands, p_t might determine the size of the externality generated by slum removal to neighbors. Much like an urban amenity, slum removal would likely be more valuable in neighborhoods where housing or land prices are higher.[12] It is likely, however, that this mechanism produces weaker incentives compared with the private case, simply because the arsonist does not gain the full value of the land, but is still subject to full punishment if caught by the police.

To simplify the model, I assume that the slum is in a private land and its removal provides utility $u(p_t)$ for the landowner. Nevertheless, one could think of an extension in which, for instance, function $u_{public}(p_t) = (1 + \omega) \times u(p_t)$ gives the utility of removal for slums in public lands, such that $\omega \in [-1, 0)$.

The typical slum in this model is already under threat of removal by a repossession claim. Therefore, potential arsonists could simply wait for a court decision on the removal. However, this decision is not guaranteed to happen any time soon and may or may not favor the landowner. With probability $\lambda \in (0, 1)$ for any given period, the court rules a decision. The landowner wins the lawsuit with probability $\theta \in (0, 1)$ and gets $u(p_t)$; otherwise, she gets nothing. Also, with probability $(1 - \lambda)$, there is no court decision and the landowner has to wait another period, such that there is no slum removal and she will have to choose again whether to wait or burn in the next iteration. Moreover, the landowner pays judicial costs c whenever she decides to wait rather than burn.

Combining all these elements, the landowner's expected utility when choosing to *wait* at time t is given by

$$E_t^W = \theta\lambda u(p_t) + (1 - \lambda)E_{t+1}^W - c \tag{1}$$

Such that E_{t+1}^W is her expected utility in $t + 1$, which is the same as moving Equation

[12] To clarify this point, one could think of the opposite side: in a poor neighborhood, slum and non-slum communities are more similar, and thus removing the former would not significantly change the neighborhood's environment from the perspective of the latter.

1 one period into the future. The superscript W indicates that this is the expected value of *waiting*.

Instead of *waiting* for a court ruling, the landowner might decide to *burn* the slum, in which case the removal is immediate and irreversible. The arsonist faces a probability β of going to jail, earning no payoff; otherwise, she gets $u(p_t)$. In either case, she pays a cost k to burn the slum, such that her expected utility of *burning* is given by

$$E_t^B = (1-\beta)u(p_t) - k \tag{2}$$

Since the slum was irreversibly destroyed and removal is no longer an option, there is no expected value for $t+1$.

To choose whether to wait or burn, in every period the agent compares the expected payoff of waiting for a legal removal (E_t^W) to that of burning the slum (E_t^B). The likelihood of choosing one over the other depends on parameters β, θ, c, and k, as well as on the path of land prices $\langle p_t \mid t \in \mathbb{N} \rangle$.

For there to exist the possibility of strategic arson, it must be true that both the probability of legal removal (θ) and of getting caught by the police (β) are sufficiently low. This does not seem far from the truth in São Paulo, where removal lawsuits can be quite long. Moreover, the probability of capturing arsonists seems to be quite low when comparing the number of arson cases that went to court in São Paulo with the arson-to-fires rate suggested by Bruno (2010). Between 2011 and 2019, the number of arson trials in court represented less than 10% of all fires, whereas Bruno (2010) suggests that 30% of all fires in the city were caused by arson.

Detailed derivations are quite similar to what is found in textbooks such as Dixit and Pindyck (1994) and are therefore deferred to the Appendix. Under mild conditions and assuming a usual distribution for the path of land prices over time, the optimal rule of decision for the arsonist hinges on p_t relative to a threshold value p^* such that she chooses *wait* if $p_t < p^*$ and *burn* if $p_t \geq p^*$. Formally, the probability of arson is given by Equation 3.

$$\begin{aligned} P(arson) &= P(p \geq p^*) \\ &= P\left\{ p \geq \hat{p} \left[\frac{\gamma(\alpha-1)}{I(1-\theta-\beta)(\gamma-\alpha)} \left(k - \frac{rc}{\lambda + r} \right) \right]^{\frac{1}{\alpha}} \right\} \end{aligned} \tag{3}$$

Such that p is the current slum land value;[13] $\hat{p}$ is the second threshold price defining the optimal timing to develop an empty land plot *after* the slum is removed; and γ and α are positive polynomial roots detailed in the Appendix.

Equation 3 provides some insights about how the probability of arson responds to institutional changes. For example, increasing the probability of either winning a repossession lawsuit (θ) or capturing the arsonist (β) increases the threshold p^*, thus decreasing the overall probability of arson, *ceteris paribus*. Analogously, increasing the cost of arson k or decreasing the cost of legal lawsuit c would both contribute to less arson cases.

The optimal threshold for developing the land plot ($\hat{p}$) is also important. Increasing $\hat{p}$ means that the landowner would postpone the decision to develop a new building in that plot. Therefore she would be more willing to wait for a court decision rather than burning the slum. Conversely, if $\hat{p}$ is low — and suppose now $\hat{p} < p^*$ —, then the landowner would have developed the plot already in the absence of the slum, which makes her more willing to commit arson.

Finally, the model implies that the relationship between arson and land value is non-linear. The empirical counterpart to this implication is that we should observe a positive probability of arson only when slums are located in neighborhoods where land value is above a given threshold. In the next sections, I describe the data and explain how I intend to test this implication.

4 Data and Descriptive Analysis

To test the relationship between land value and the probability of arson, I rely on information about the location of slums, the number of fires in each of them, and the estimated value of the land they occupy. In the following subsections, I provide details about these different pieces of information.

4.1 Slums

The municipal government of São Paulo provides geocoded, cross-sectional data for 2,009 slums in the city during the 2001-2003 period. Apart from polygons, the data also document the year of foundation of each slum and whether legal ownership of the land is private, public (government), or unknown. In this setting, slums are defined as precarious and spontaneous settlements with no planning of street or plot layout, no land property

[13] Time period t is no longer in notation because I solve the model for the continuous rather than discrete case.

rights, poor infrastructure, and mostly composed of self-constructed houses inhabited by low-income families (Prefeitura de São Paulo, 2022).

Using a spatial merge, I also add information from the 2000 Brazilian Census to these polygons, such as number of residents and households, income, access to water, sewage, and trash collection. Table 1 provides some descriptive statistics at the slum level. However, one should interpret Census variables as neighborhood rather than slum characteristics, because Census Tracts and slum polygons rarely coincide perfectly.[14] This explains, for instance, high shares of access to piped water, bathroom, and trash collection.

Table 1: Descriptive Statistics of Slums and Neighborhood in 2000

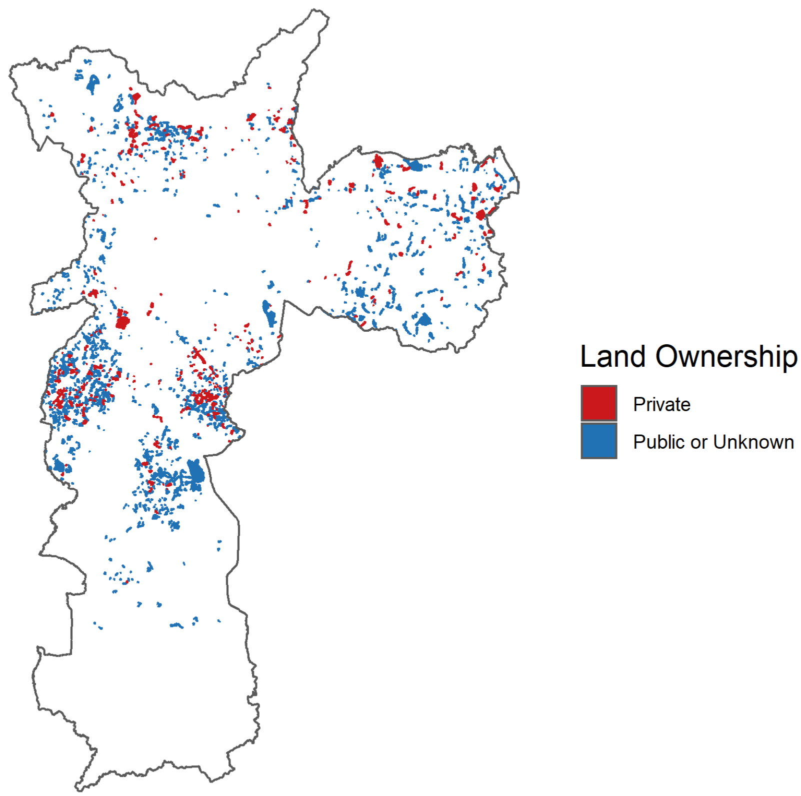
	Mean	S.D.	Median
Census			
Share Piped Water	0.96	0.12	1.00
Share with Bathroom	0.98	0.06	1.00
Share Trash Collection	0.97	0.08	1.00
Share Low Income	0.41	0.11	0.42
Residents per Household	3.78	0.29	3.79
Households per Hectare	1459.68	2995.17	539.51
Municipal Government			
Area in Hectares	1.40	4.53	0.46
Share Landslide Risk	0.22	0.31	0.00
Share Private Land	0.23	0.42	0.00
Year Occupation	1976.98	9.92	1977.00

Figure 1 shows the location of slums and the legal ownership of their land. Overall, slums in private and public lands are fairly well distributed across the entire city. Furthermore, around 10% of slums have no information on land ownership. These are not necessarily cases with missing information, since it is rather common in Brazil for land to have unknown ownership.[15] Throughout the paper, I will treat these lands as public and include them in the analysis to improve precision. This does not seem to be a strong assumption, since private owners should have more incentives to claim their property and prevent them from falling into the *unknown* category.

[14] To merge Census variables to slums, I create weights proportional to the area of intersection between slums and each census tract.

[15] According to Freitas et al. (2018), one cannot identify land ownership for almost 20% of the Brazilian territory.

Figure 1: Spatial Distribution of Slums in São Paulo in 2001-2003 Period and Land Ownership

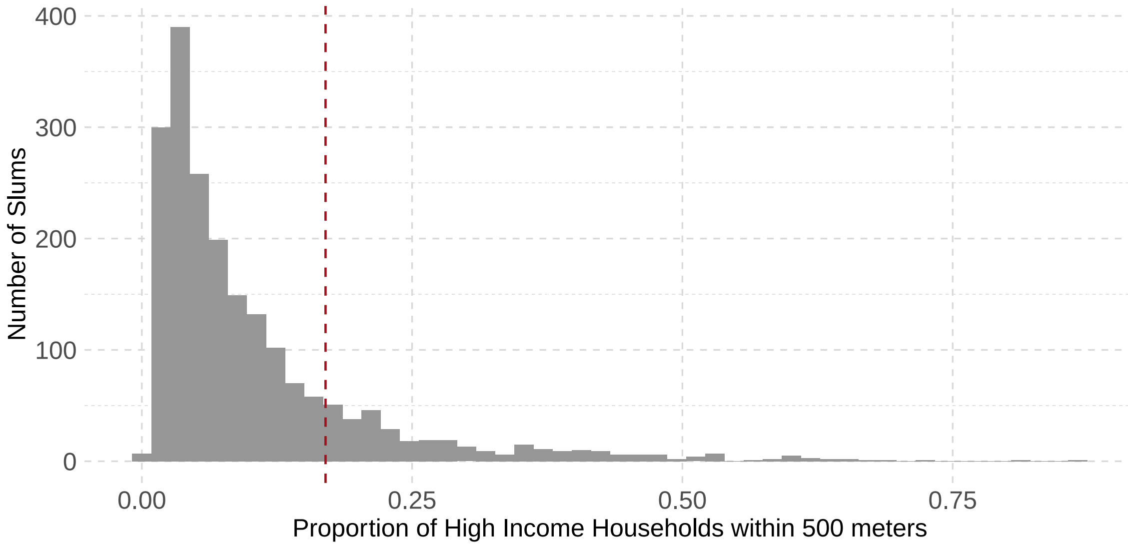


Notes: "Private" includes lands that are entirely or partially owned by private agents. "Public or Unknown" includes both lands owned by any level of government and those whose ownership is missing.

Figure 1 also reveals that few slums are located in central areas of the city. This is not to say, however, that slums are only present in poor areas, because São Paulo has expanded substantially and rather unevenly since the 1980's. Rich households have occupied the southwestern and western portions of the city, causing slums and expensive neighborhoods to frequently share boundaries.

To illustrate this, Figure 2 shows the distribution of high income households near slums in 2000. As expected, most slums are in neighborhoods with relatively few high income households. Nevertheless, for almost one fifth of slums in São Paulo, the share of high income households around them is higher than the city average. This suggests that there is a significant number of slums located in relatively rich neighborhoods.

Figure 2: Distribution of Slums According to Proportion of High Income Household Heads Around Them in São Paulo (2000)



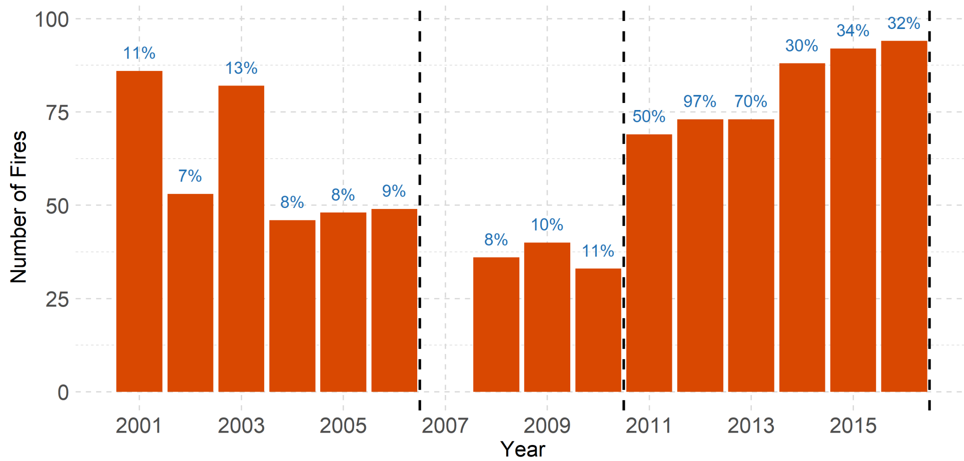
Notes: Data from the 2000 Census. High income household heads are defined here as those earning more than 10 times the Brazilian minimum wage. The city average proportion of high income households is represented by the vertical dashed red line.

4.2 Fires

Data on fires range from 2001 to 2016, comprise the entire state of São Paulo, and were provided by São Paulo State Fire Department (COBOM-SP). All observations inform whether the fire happened in a slum or not, as well as the address of the event. Due to some changes in recording methodology, the database was divided in three periods by the fire department: (i) 2001-2006; (ii) 2008-2010; and (iii) 2011-2016. Data for 2007 is missing entirely from the archive. Moreover, address information is less precise for period (ii), because the name of the municipality is missing. Instead, I have access to municipal district names, which are not unique across municipalities in the state.

Figure 3 presents the number of slum fires in each year, as well as the three breaks in the data.

Figure 3: Slum Fires in São Paulo from 2001 to 2016 and Changes in Data Structure



Notes: Percentages in blue on top of each bar are a measure of accuracy for the geocoding procedure. They indicate the proportion of geocoded fires in sample compared with total number of fires in the state of São Paulo in each year.

One concern is that missing municipal names could make geocoding success rates in group (ii) lower than in the others. This, however, does not seem to be the case when comparing groups (i) and (ii). Above each bar in Figure 3, I present the success rate for each year. This is given by the number of slum fires successfully geocoded divided by the total number of slum fires in the state of São Paulo,[16] i.e., the total number of slum fires before geocoding the observations. Indeed, the success rate in geocoding is fairly comparable, around 10%, from 2001 to 2010.

Conversely, accuracy increases substantially from 2011 through 2016. One potential problem is that the increase in the number of fires observed after 2010 could be associated to higher precision in geocoding. Although inconvenient, this sort of problem is expected when working with data on slums. Even when authorities are fully committed with producing high-quality data, observing phenomena in informal settings is hard.

For the empirical exercises in this paper, such aspect of the data is not necessarily a problem, as long as the increase in accuracy is affecting all slums regardless of their land value. To mitigate potential issues, I will include year fixed effects in all specifications. I will also run tests restricting the sample period to assess the responsiveness of results to changes in the geocoding success rate.

[16] I have to consider slum fires in the entire state because the names of municipalities are missing for group (ii).

4.3 Slum Land Value

Assessing the value of slum-occupied land evokes again the challenge of working with data on informal settings. Because there is no direct measure of these land prices, I rely on proxies calculated from formal housing market data. The main variable used in this paper is the Floor-to-Area Ratio (FAR)[17] of formal residential and non-residential units within 500 meters of slums' polygons.

Although an indirect measure, FAR is expected to be strongly and positively correlated with land value. This is both a result from canonical urban economics models and empirical investigations, such as Brueckner and Singh (2020). Essentially, the scarcer the land — higher prices — the more intensive will be the use of capital — floor-to-area ratios.

I also use Assessed Property Value as an alternative proxy in some robustness analyses. Because assessed values are government estimates of house prices for tax purposes, they are also not a direct measure of land value, but should be correlated with it (Wen and Goodman, 2013). In São Paulo — as in many cities in Brazil — these assessed values are calculated based on government-defined values per square meter for each property in the city. These baseline values are estimated using not only past market transactions reported to the government, but also some construction and location parameters.[18]

Although assessed values may sound like a more natural proxy for land value, they are subject to much more government discretion than FAR. Because assessed values affect property taxes directly, municipal governments have political incentives to choose when to update such values strategically. More than once during the sample period, assessed values had long periods of stagnation followed by large increases that do not correspond to market dynamics, but are rather rooted in political decisions. Conversely, FAR is naturally updated as floor space increases in the city and does not depend on a political decision. Hence, I use FAR as the main proxy for land value throughout the paper. For the interested reader, I present results based on assessed values in the Appendix.

I construct proxies for slum land value according to the formula in Equation 4.

$$SlumValue^{r}_{st} = \frac{\sum_{i=1}^{I} \mathbb{1}[distance(i,s) \leq r] \times Proxy_{it}}{\sum_{i=1}^{I} \mathbb{1}[distance(i,s) \leq r]} \tag{4}$$

[17] Total floor space divided by total plot area.

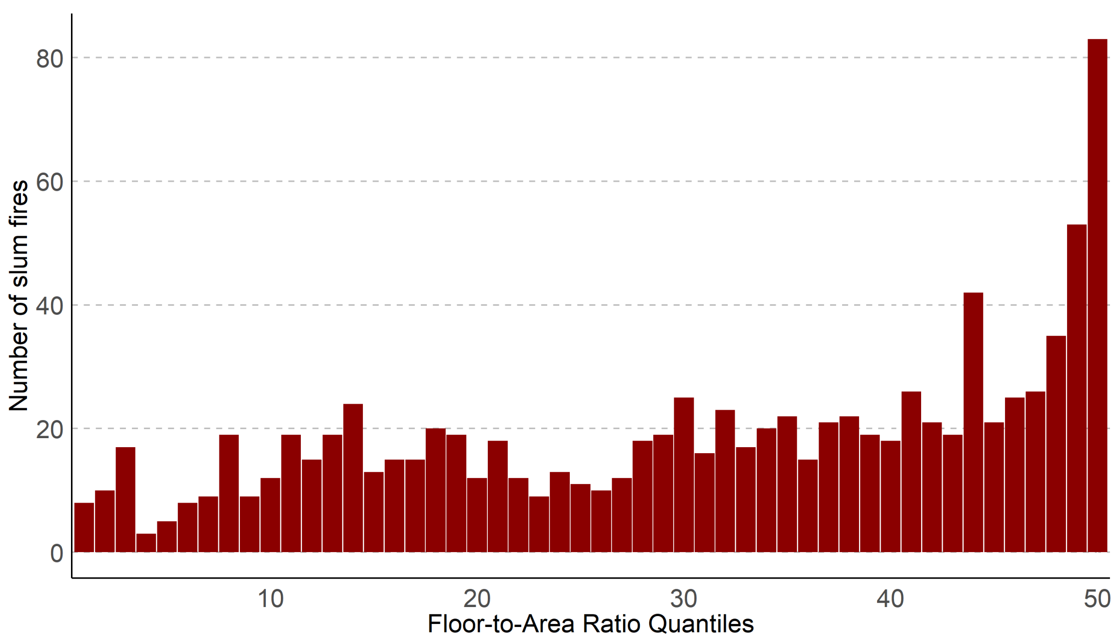
[18] For example, the baseline value for commercial properties is inherently different from that of residential ones; moreover, it could also depend on the quality of materials used in construction; or on the typology of the construction, such as multi-family or single-family. Apart from having these pre-defined baselines for each category, property values are also discounted by factors accounting for depreciation, for example.

Such that $SlumValue^r_{st}$ is the inferred land value of each slum s, $Proxy_{it}$ is the Floor-to-Area Ratio of each formal property i at time t. Group I is the universe of formal properties in Sao Paulo and $distance(i, s)$ is the distance in meters between formal property i and the border of slum s. Moreover, r is the radius of a buffer around slum s, which I set to 500 meters in all analyses. Hence, slum land value the average of $Proxy_{it}$ using only formal properties that are within r meters of each slum s.[19]

4.4 Combining the Data

Figure 4 presents the distribution of slum fires across fifty quantiles of Floor-to-Area Ratio, the proxy for slum land value. It shows that the number of fires increases with slum land value and it does so in a non-linear fashion. While the average number of fires is roughly between 10 and 20 over most of the distribution, it increases sharply in the top quantiles. In particular, the fiftieth quantile is responsible for almost 10% of all fires in the city.

Figure 4: Number of fires by quantiles of average real formal property value around slums, Sao Paulo (2001-2016)



Notes: Quantiles are calculated separately for each year. For example, the same slum can be in quantile 20 in one year and 25 in another.

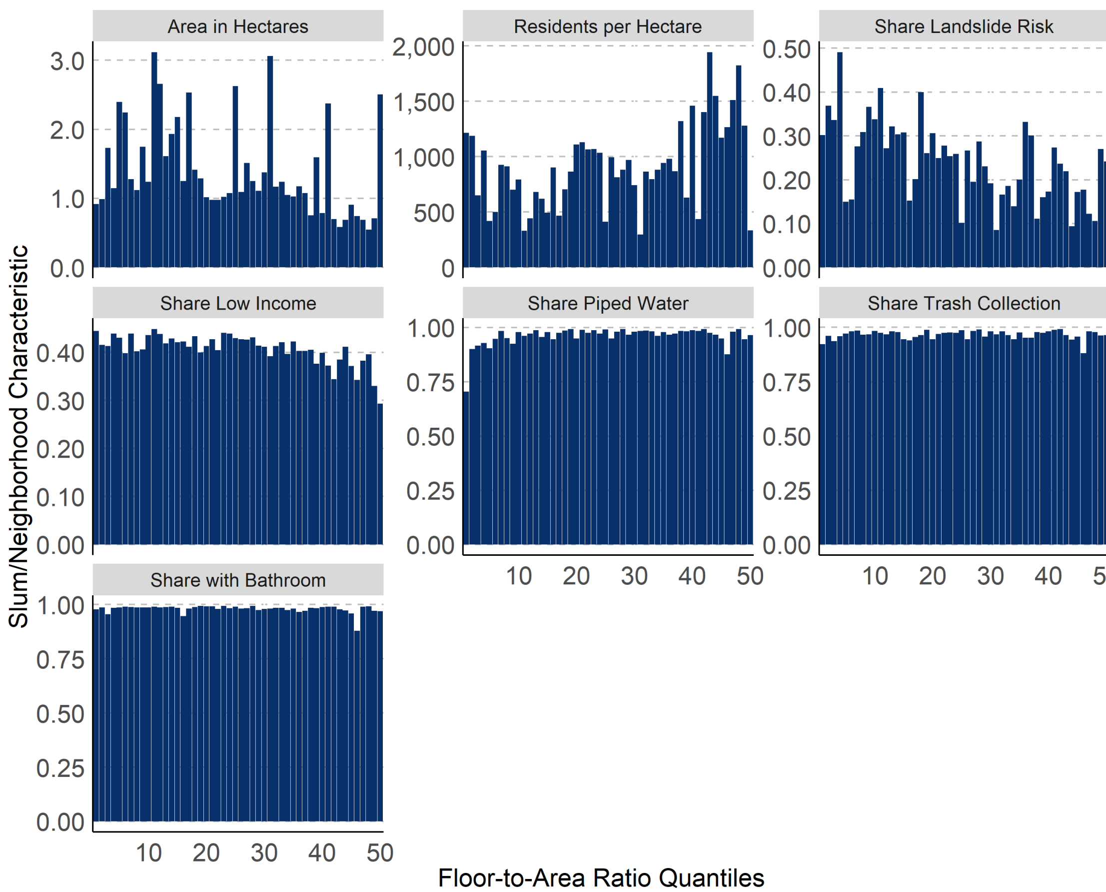
Although this figure does not show a direct measure of arson, it suggests a discontinuity in the distribution of fires that is consistent with the strategic arson hypothesis.

[19] For further details about this calculation, please refer to the Appendix.

As discussed in Section 3, if strategic arson is happening, we should observe a positive probability of arson only after a given land value threshold.

The main competing hypothesis that could explain this pattern is that slums at the top of the land value distribution are disproportionately larger, denser, newer, or have worse infrastructure — all of which could drive a larger number of accidental fires. Figure 5 shows the distribution of neighborhood characteristics that are correlated with those potential confounders. As opposed to fires, the distribution of these characteristics is much smoother. Even though some variables increase with land value, such as residents per hectare, there does not seem to be a discontinuity similar to the case of fires. This suggests that the abnormal frequency of slum fires in the highest quantiles of land value is not simply a mechanical consequence of worse infrastructure or higher density.

Figure 5: Slum and Neighborhood Characteristics and Quantiles of Floor-to-Area Ratio in 2001



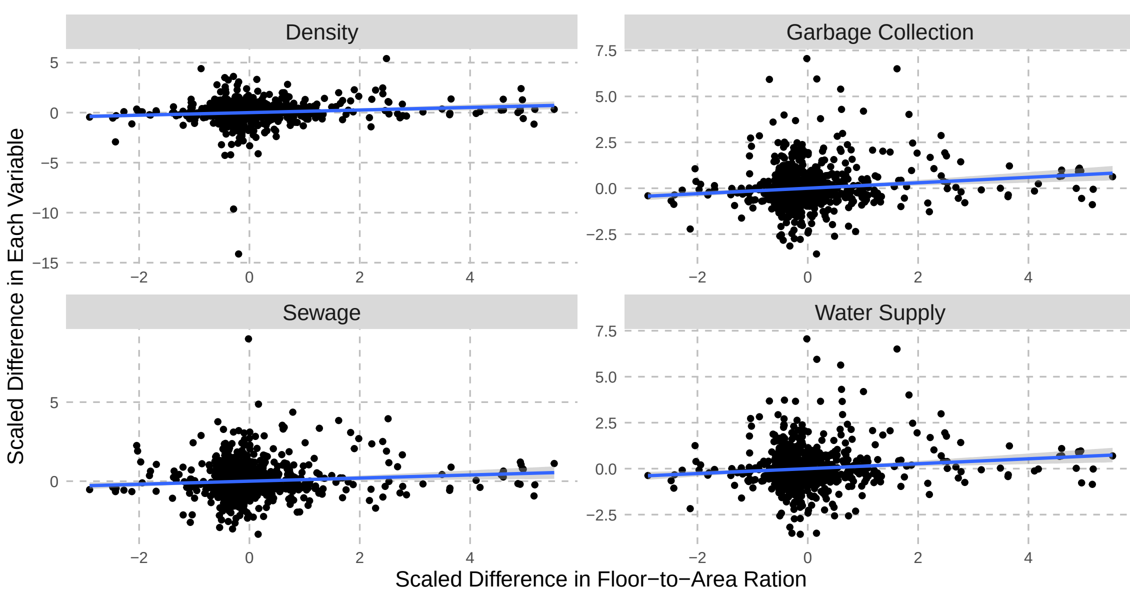
Notes: Slum characteristics from cross-section in 2001-2003 include age, area, and share of slum under landslide risk. Neighborhood characteristics from 2000 Census include residents per hectare, coverage of piped water and trash collection, share of households with bathroom, and share of household heads earning up to 3 times the Brazilian minimum wage.

Alternatively, fires could be driven by the sorting of either slum residents or worse infrastructure into neighborhoods where land value increased. This is not captured by the static characteristics shown before and could be behind the skewed distribution of slum fires presented in Figure 4.

However, this does not seem to be the case in this context. Figure 6 shows correlations between changes in slum density or infrastructure and changes in land value, measured by floor-to-area ratio. The figure shows scaled differences between variables observed in 2010 and 2000. To calculate these differences, I use Census data, which cover a fraction of the slums in my sample, but contain more information about number of residents and public service coverage. Moreover, I focus on slums that existed both in 2000 and 2010.[20]

Looking at these indicators of density and infrastructure, there does not seem to be a positive correlation between them and land value. This suggests that vulnerability to more accidental fires is not increasing in slums located in more expensive neighborhoods, which corroborates the hypothesis that something else is driving the abnormal distribution of fires presented in Figure 4.

Figure 6: Increase Slum Density and Infrastructure and Changes in neighboring Floor-to-Area Ratio between 2000 and 2010



Notes: Scaled differences are calculated by calculating the level of each variable in 2010 minus its level in 2000 and then normalizing the result. All variables come from Census data, which do not map all slums in our main sample. This figure shows differences for 993 slums that existed both in 2000 and 2010.

After presenting some descriptive evidence of strategic arson, we now move to the

[20] I refrain from using this data to identify slum creation, because technological improvements allowed for more slums to be mapped in 2010 than in 2000.

two empirical approaches trying to identify the relationship between land value and fires.

5 Cross-sectional Approach

5.1 Empirical Strategy

The first empirical exercise compares the probability of fire across slums in São Paulo with different land values, but otherwise similar observable characteristics. Based on the theoretical model's predictions, I will test not only whether fires are positively affected by land value, but also whether this effect is non-linear. To accomplish this, I will explore variation coming from slums in different quantiles of the land value distribution.

The main challenge is that no direct measure of arson is available. Instead, the data contain all sorts of fires, including those that are accidental and thus have nothing to do with strategic arson. This can cause omitted-variable bias if accidental fires are also correlated with slum land value.[21] For example, slums in higher-value land might be denser because residents want to be closer to job opportunities. This would mechanically increase the probability of fire simply due to more people causing accidents.

To deal with this, I include variables accounting for heterogeneous fire hazard across slums in different quantiles of land value. These control variables are also split in quantiles to allow for non-linear effects. Hence, identification stems from unconfoundedness conditional on observables. I rely on the assumption that the covariates included in the empirical model account for all factors that cause accidental fires and are correlated with land value.

I also assume that slums with higher probability of fire are not sorting into higher-value land. As shown in Figure 6, residents do not seem to be moving to slums in higher-value neighborhoods over time. Moreover, the sample covers the 2001-2016 period, whereas slums were largely built prior to 1990. Therefore, I assume slum residents had limited information on the distribution of future land prices across the city by the time they decided to establish the slum.

To deal with varying accuracy in the geocoding procedure, as discussed in Section 4.2, not only do I add year fixed effects, but also calculate the quantiles of land value within each year. This means that almost all of the variation in land value and probability of fire is coming from the cross-section, thus avoiding the consequences from comparing different periods.

[21] Alternatively, one can think of this as a non-classical measurement error problem.

Finally, I explore heterogeneous incentives to commit strategic arson in private and public squatted lands. I expect the effect of land value on fires in private slums to be stronger than in public ones. Since land ownership is unlikely to be driven by potentially omitted variables discussed above, comparing slums in private and public lands should provide an additional source of exogeneity for identifying the effect on strategic arson.

Given the identification assumptions and the challenges described above, Equation 5 presents the regression model to be estimated.

$$
\begin{aligned}
ProbFire_{st} = & \sum_{k \in [1:K],\, k \neq k_0}^{K} \delta_k \mathbb{1}[QuantileSV_{s,t} = k] \times Private_s \\
& + Private_s + \sum_{k \in [1:K],\, k \neq k_0}^{K} \phi_k \mathbb{1}[QuantileSV_{s,t} = k] \\
& + X_s \times \tau_t + DistrictYear_{st} + \epsilon_{st}
\end{aligned} \tag{5}
$$

i.e., the probability of fire in slum s at time t, $ProbFire_{st}$, is a function of that slum's position in one of the K quantiles of slum land value. This is represented by the sum of dummies $\mathbb{1}[QuantileSV_{s,t} = k]$, indicating whether slum s is at quantile k at time t. The expression $k \in [1 : K]$, $k \neq k_0$ simply states that one of the quantiles is excluded from the equation to avoid collinearity. Index $Private_s$ denotes whether a slum is occupying private land, and interacting it with quantiles provides the differential effect of land value on private versus public slums.

Vector X_s is a set of constant slum and neighborhood characteristics prior to 2001 that can both explain accidental fires and be correlated with land value. I divide the following covariates in the same number of quantiles as the main independent variable: number of formal units per hectare within 500 meters of slum, area of slum in hectares, residents per household, and households per hectare. Furthermore, I add the following covariates without breaking them into quantiles, because there is not enough variation to form unique groups: share of households with access to piped water, trash collection and in-house bathroom; share of heads of households with monthly income up to 3 times minimum wage; and share of slum under risk of landslide.

I include all covariates to account for initial conditions, but I also interact them with year fixed effects to capture changes in their contribution. I also include District-Year fixed effects, which should not only capture localized trends across the 96 districts of São Paulo, but also restrict comparison to slums that are close to each other.

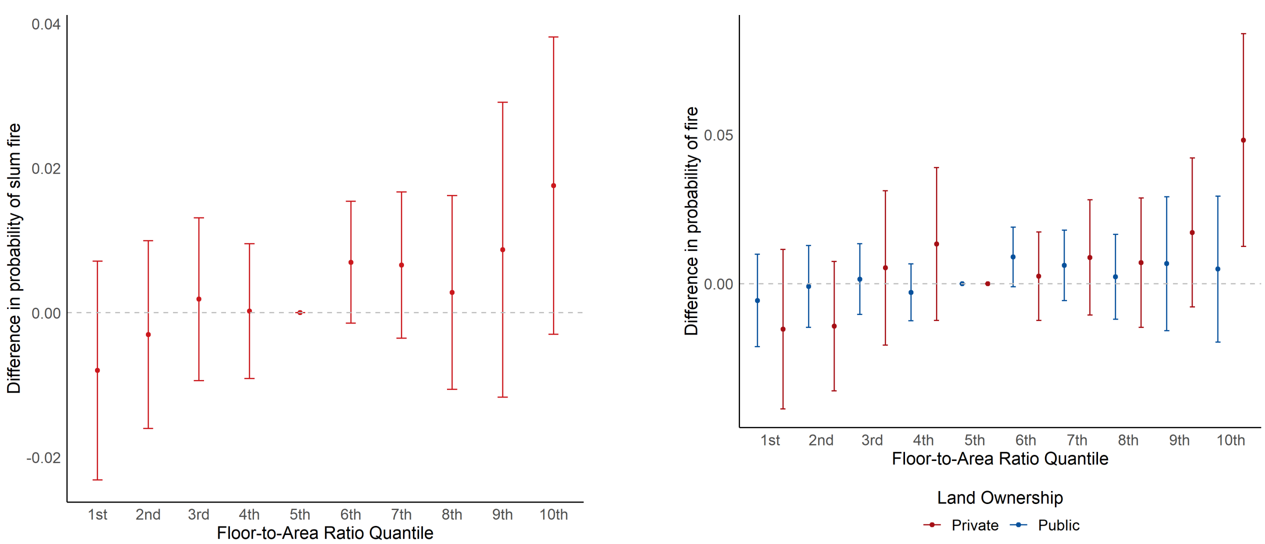
The coefficients of interest are the δ_k and the ϕ_k, which provide insights on three features of the data. First, whether slums in higher quantiles are abnormally affected by fires, which would corroborate strategic arson. Second, whether the non-linearity we observed in the descriptive section is statistically significant after the inclusion of controls. Third, δ_k tests whether the effect is different for slums in private lands.

From the theoretical framework, I expect coefficients to be statistically significant only above a given threshold quantile k^*, but indistinguishable from zero below that. Moreover, as discussed before, the result should be mainly driven by slums in private lands.

5.2 Results

Figure 7 shows estimates for Equation 5 including all covariates mentioned in the previous section. Panel 7a shows the average effect for all slums, regardless of who is the owner of the land. In line with theoretical predictions, the probability of fire is higher precisely in the highest quantile, whereas it is indistinguishable from zero for lower quantiles.

Figure 7: Estimated Difference in Probability of Fire across Floor-to-Area Ratio Quantiles with Full Set of Controls, 2001-2016



(a) Difference in Probability of Fire for All Slums

(b) Difference in Probability of Fire for Slums in either Private or Public Land

The average effect, however, is only significant under a 10% threshold. The lack of precision arises from bunching public and private lands. As illustrated in Panel 7b, accounting for land ownership is key. In this case, the regression model is the same as before, except now I include dummies indicating whether the land is private or public and I interact them with quantile indicators. Results show that the probability of fire is significantly different across private and public slums, specifically in the highest quantile of the land value distribution and even after controlling for other factors causing fires. This indicates, as anticipated, that incentives to strategic arson are stronger in private lands. In fact, there is no evidence of fires related to land value in public lands.

Figure E.1 in the Appendix presents results using property value quantiles instead of floor-to-area ratio. Although noisier, estimates form a similar shape, with an abnormal probability of fires for slums in private land and in the highest quantile.

One might be concerned with the decision of how many quantiles to use. To alleviate this, I propose an exercise to find where lies the discontinuity in the probability distribution of slum fires across land values. To do this, I create separate samples for private and public slums. Then, I break the land value proxy in one hundred quantiles. Finally, I estimate the model in Equation 6 below for these one hundred quantiles.

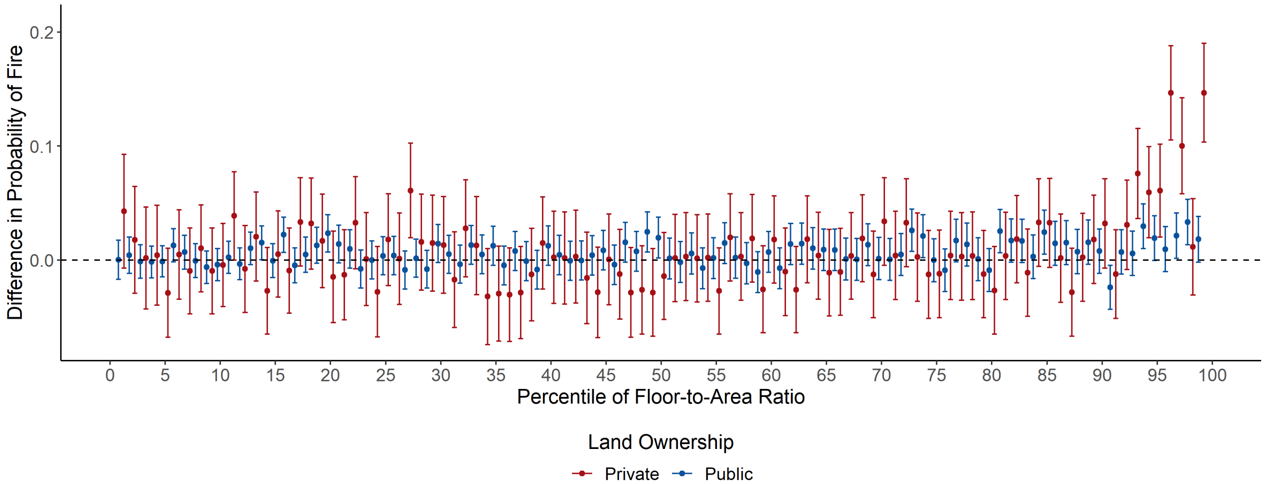
$$ProbFire_{st} = \beta_1 \mathbb{1}[QuantileSV_{s,t} = k] + \tau_t + \epsilon_{st} \tag{6}$$

The difference with respect to Equation 5 is that now I want to compare each quantile to all previous ones, instead of one single baseline. For example, for quantile 5, the indicator is equal to one if slums are in quantile 5 or zero if they are in quantiles 4 or lower. I exclude all observations in quantiles above 5. For one hundred quantiles, I estimate Equation 6 multiple times — i.e., for $k \in [2 : 100]$ — restricting observations such that only quantiles $j \in [1 : k]$ are included in each sub-sample. I estimate this model for public and private slums separately because quantiles differ across these two groups. Moreover, since there are too many quantiles, I only include year fixed effects τ_t in the set of covariates.

This test should point to potential discontinuities in the probability distribution of fires over land values. If the probability of fire increases smoothly, there should be no significant differences between each additional quantile and the average of the previous ones.

Figure 8 presents the estimated coefficient β_1 for each quantile $k \in [2 : 100]$.

Figure 8: Difference in Probability of Fire for Slums in either Private or Public Land - Comparing each Quantile with Previous Ones

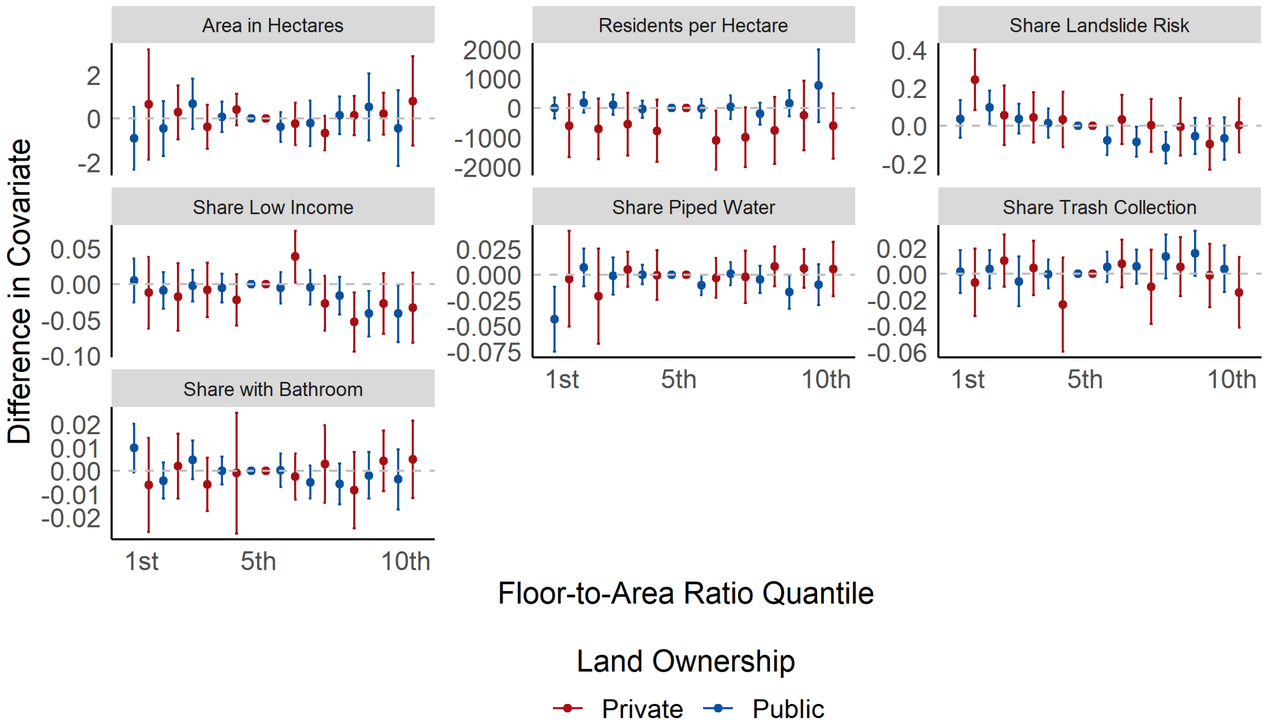


Notes: Each point and interval in this figure comes from the same specification estimated for increasingly larger sub-samples. For quantile 5, for example, the model includes all observations located in quantiles 1 through 5, but none above 5.

The estimated difference in the probability of fire is significantly different from zero only for slums in private land that are above the 90^th of land value. This indicates that there is some discontinuity around this quantile, which is in line with the estimation using only 10 quantiles. Moreover, it reinforces the theoretical prediction of a threshold land value above which strategic arson is profitable for landowners.

Finally, Figure 9 replicates the model from Figure 7b, except that the dependent variables are some of the covariates used to measure slum infrastructure. As opposed to what happens with fires, there is no significant difference in infrastructure across quantiles, especially when analyzing slums in private versus public lands. This adds credibility to the assumption that fire hazard is comparable across these groups of slums within quantiles and it suggests that accidents are not driving the results for slums in private land.

Figure 9: Regression of Main Covariates on Quantiles for Slums occupying Private and Public Lands



Notes: Regressions estimated with same specification as Figure 7b for each selected covariate, except that observations are restricted to Census Year 2000.

In summary, evidence from the cross-sectional approach point to an abnormal discontinuity in the probability of fire specifically for slums in private lands. This does not seem to arise from differences in slum infrastructure, but rather from economic incentives. In the next section, we verify whether the same conclusion for a more local difference-in-differences exercise exploring variation across groups of slums and over time.

6 Difference-in-Differences

6.1 Brief Context

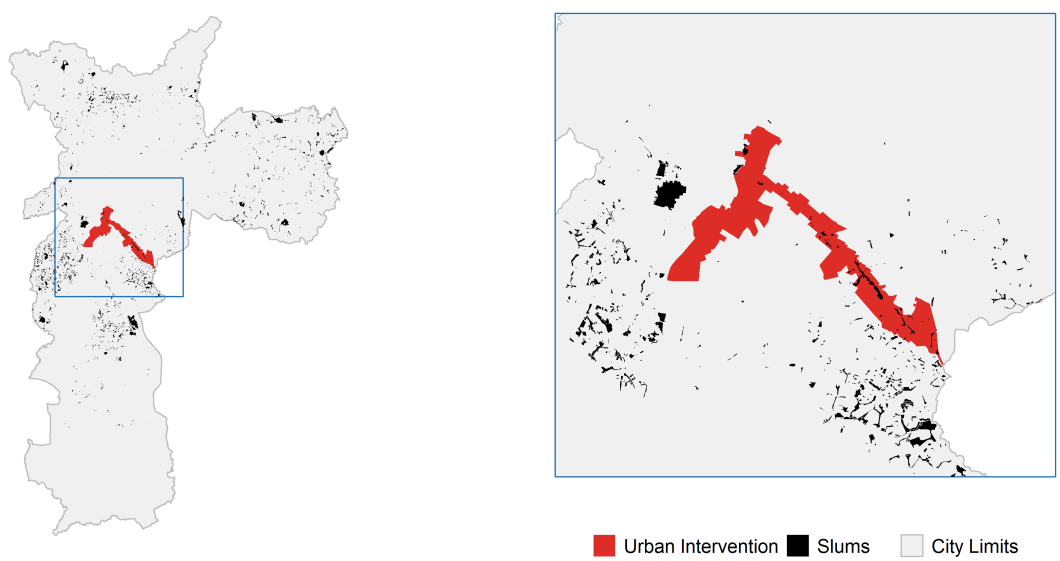
Cross-sectional estimates suggest that strategic arson may be happening in slums built on private lands, but not in those built on public lands. There might be, however, concerns about other potentially omitted variables driving the abnormally high probability of fire in high-value slums.

On the one hand, such potential confounding factors would need to be quite specific. Not only would they be uncorrelated with the observable characteristics included in the model, but also simultaneously associated with high land value and with the fact that slums are in private land. On the other hand, it is true that the model is limited in terms of controlling for all initial slum conditions.

To improve identification, I run an alternative analysis using a difference-in-differences model. I explore a large shock on land value caused by *Operação Urbana Água Espraiada* project in São Paulo. This intervention implemented an auction mechanism to fund improvements in urban infrastructure for a small set of neighborhoods that were still a bit far from the main business centers in the city. As a result, it also boosted the demand for land, conceivably causing slums in the area to become more valuable for real estate development purposes.

Figure 10a shows the location of urban intervention *Água Espraiada* in São Paulo, occupying approximately 13 square kilometers, or little less than 1% of the city's area. Figure 10b details all slums within a 4-kilometer radius of the intervention. Out of 546 slums in this region, 62 were inside the perimeter of *Água Espraiada*.

Figure 10: Urban Intervention Água Espraiada and Slums in Sao Paulo



(a) Urban Intervention Água Espraiada (b) Slums within 4 kilometers of Água Espraiada

The intervention consisted of a series of public auctions starting in 2004, in which the municipal government sold permits for developers who wanted to build above zoning restrictions inside the intervention zone.[22] The government would then spend these funds

[22] The initiative was regulated in 2001 by Municipal Law 13.260, but it was effectively implemented after the first auctions, in 2004.

in urban improvements such as new bridges and parks, more public transit services, wider avenues etc.

This region was not completely under-served prior to the intervention. Previous projects had already expanded its main avenue during the 1990's, removing some slums, and attracting new people to the area. However, investments slowed down until the new urban intervention initiated in 2004, bringing significant and visible changes, especially in terms of road infrastructure and public transit (Nobre, 2009).

One important aspect of this policy is that all funds raised from the auctions were required to be re-invested inside the intervention zone. Hence, land value is expected to have increased not only thanks to higher demand, but also due to better amenities.

Figure 11 shows the additional floor space that was allowed to be constructed after the auctions. There are two periods of substantial increase: one going from 2005 to 2010 and another one going from 2012 to 2014. The amount of potential floor space exceeding zoning restrictions by the end of 2016 represented 20% of the intervention zone's area.

Figure 11: Stock of Additional Floor Space Created Inside Urban Intervention *Água Espraiada*

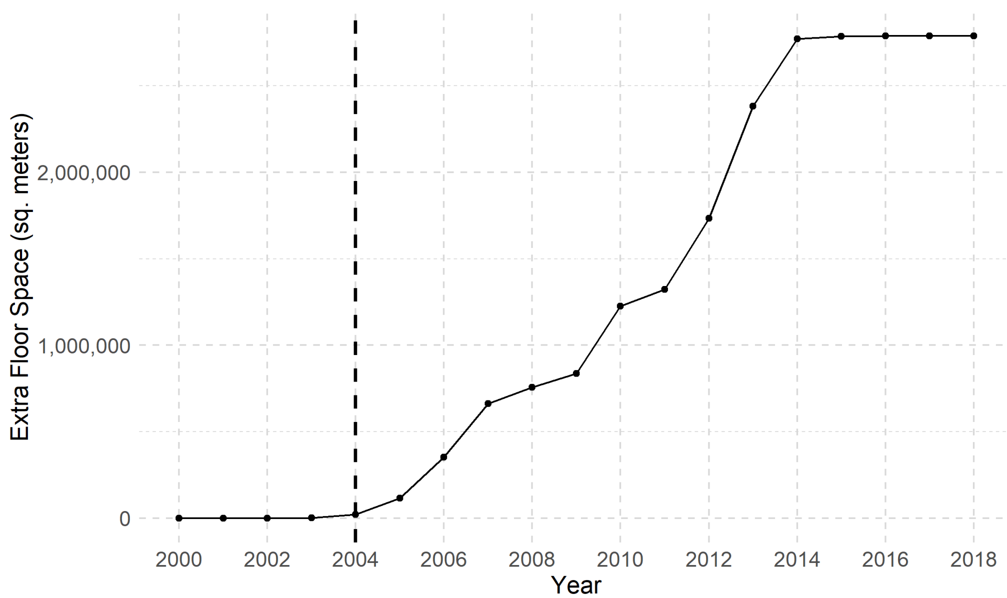
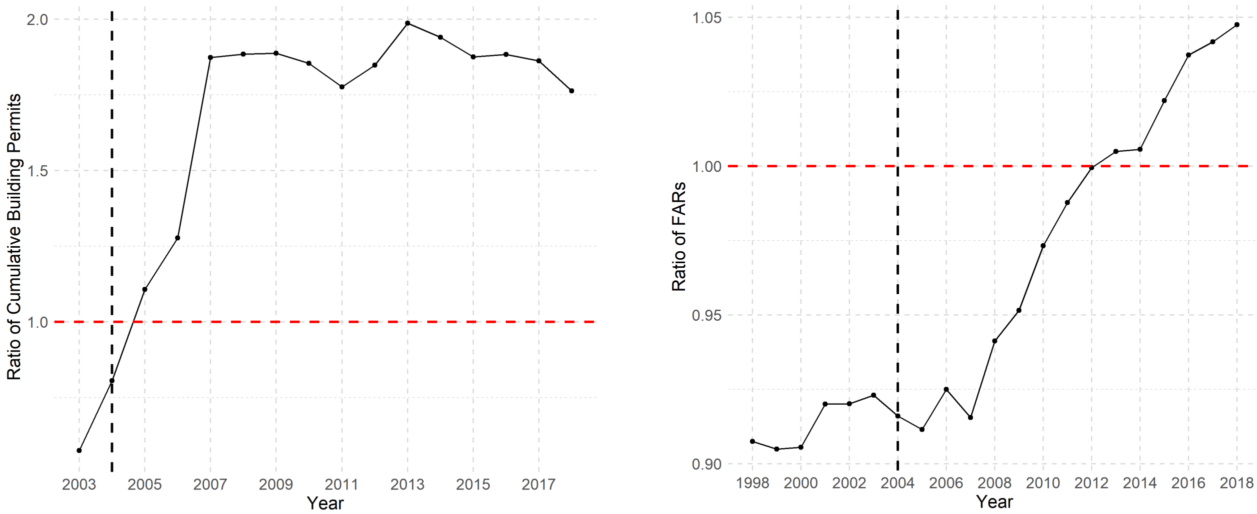


Figure 12 presents how the local land market reacted to the urban intervention. Figure 12a shows the stock of requests for building permits inside *Água Espraiada* compared with neighboring areas within 4 kilometers.The y-axis shows the ratio between the stock of requests inside *Água Espraiada* and the stock outside the intervention, but within 4 kilometers. This illustrates how fast the demand for building permits increased in a short period. In 2003, the stock of permit requests inside *Água Espraiada* was 50% lower compa-

Figure 12: Building Permits, Floor-to-Area Ratio, and Urban Intervention Água Espraiada



(a) Ratio of Stocks of Building Permit Requests Inside and Within 4 Kilometers of Urban Intervention Água Espraiada

(b) Ratio of Floor-to-Area Ratios Inside and Within 4 Kilometers of Urban Intervention Água Espraiada

red with neighboring areas. In 2007, requests inside *Água Espraiada* were almost twice as large as those outside the intervention.

This rapid growth in demand led to an increase in urban density a few years later. Figure 12b shows that the FAR inside *Água Espraiada* went from 10% below to 5% above the FAR outside the intervention zone. Combined, both panels in Figure 12 suggest that land value inside *Água Espraiada* increased fast after 2004 compared with neighboring areas.

6.2 Empirical Strategy

With a Difference-in-Differences model, I explore both the timing of *Água Espraiada* intervention and the fact that slums inside its perimeter — the treated group — were relatively more exposed to the shock in land value compared with those further away from the intervention zone — the control group. In my main specification, the latter includes slums that are further than 500 meters from Água Espraiada and within 4 kilometers of it.

These thresholds serve two purposes. First, I discard slums that are too close to the intervention to avoid contamination. Second, I define a maximum distance to keep treated and control groups more comparable. Intuitively, slums that are closer too each other should be more similar in terms of accessibility, infrastructure, density etc. In the Appendix, I show that results are fairly stable under different threshold definitions.

The empirical model is given by Equation 7:

$$ProbFire_{st} = \beta_1 InsideUrbanIntervention_s \times I_{t\geq 2005} + \lambda_s + \tau_t + X_s \times \tau_t + \varepsilon_{st} \tag{7}$$

such that $ProbFire_{st}$ is an indicator of whether slum s was hit by a fire in year t, as before; λ_s are slum fixed effects to control for initial conditions and other unobservable, time-invariant characteristics; X_s is a vector of constant slum and neighborhood characteristics, which I interact with year fixed effects τ_t to control for changes in slum infrastructure and density over time. The treated group is indicated by $InsideUrbanIntervention_s$ and the treatment period is defined by $I_{t\geq 2005}$. Because I only have yearly data and the intervention started in July of 2004, I define 2005 as the first full year of treatment.

We are interested in coefficient β_1, which measures the effect of the urban intervention on the probability of fire in treated slums compared with the control group. Since I am exploring *Água Espraiada* as an instrument affecting the land market, β_1 is essentially capturing the effect of higher land value on the probability of fire for those slums inside the intervention area. Hence, if strategic arson is really happening at scale, we should observe a positive and significant estimated $\hat{\beta}_1$.

The main identification assumption here is that land prices would have evolved similarly in treated and control slums had *Água Espraiada* not happened. As a consequence, urban land conflicts leading to strategic arson would also have evolved similarly in both groups, in the absence of treatment.

Although I restrict my sample to slums that are relatively close to each other, observable characteristics across units inside and outside the perimeter of *Água Espraiada* may still differ. To improve balance in such characteristics between treated and control groups, I employ an Inverse Probability Weighting (IPW) algorithm, following Hirano et al. (2003), Busso et al. (2014), and Cunningham (2021).

In summary, first I run the probit model in Equation 8 to estimate the probability of treatment $\hat{p}$ as a function of observable covariates.

$$Prob(Treated_i = 1|X_i) = \Phi(X_i\alpha) \tag{8}$$

such that $\Phi(\cdot)$ is a standard cumulative Normal distribution and α is a vector of coefficients estimated by maximum likelihood. For the sake of brevity, the estimated propensity score models for private and public slums are presented in Appendix Tables D.1 and D.2, respectively.

Then, I use the estimated propensity scores $\hat{p}$ to re-weigh the main regression model from Equation 7. I attribute weights $1/\hat{p}$ to treated units and $1/(1-\hat{p})$ to control ones. Moreover, I remove any observation with $0.05 \leq \hat{p} \leq 0.95$ to avoid over-weighing some observations (Cunningham, 2021).

Table 2 shows balance in observable characteristics for both the unmatched and matched samples. Here, I focus on **private slums**, because they are the ones driving the results, but an analogous comparison for public slums is available in Appendix Table D.3.

As one may observe, there are substantial differences between slums inside and outside *Água Espraiada* before using IPW. After re-weighing observations and trimming propensity scores with extreme values, we are left with a more comparable sample, on average. Additionally, the interested reader may also find the distribution of propensity scores for both treated and control groups in Appendix Figure D.1.

Table 2: Propensity-Score Matching Balance Test for Slums in Private Land inside or within 4km of Urban Intervention

	Unmatched			Matched		
	Treated	Control	Difference	Treated	Control	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Households per hectare	767.317	1715.84	-948.523	1041.487	682.611	358.876
			(582.126)			(196.81)
(log) Slum Area	-0.513	-1.034	0.521	-0.933	-0.675	-0.258
			(0.257)			(0.285)
(log) Neighborhood F.A.R.	-0.343	-0.783	0.44	-0.445	-0.418	-0.028
			(0.07)			(0.067)
(log) Neighborhood Property Value	4.884	4.409	0.476	4.76	4.768	-0.008
			(0.084)			(0.094)
Residents per Household	3.813	3.729	0.084	3.748	3.721	0.027
			(0.062)			(0.062)
Share Bathroom	0.992	0.987	0.005	0.994	0.993	0.001
			(0.007)			(0.004)
Share Income up to 3 Salarios Minimos	0.451	0.402	0.049	0.411	0.402	0.01
			(0.023)			(0.026)
Share Landslide Risk	0.027	0.203	-0.175	0.008	0.008	0
			(0.061)			(0.014)
Share Trash Collection	0.983	0.979	0.005	0.991	0.986	0.004
			(0.01)			(0.008)
Share Water	0.991	0.982	0.009	0.994	0.993	0.001
			(0.008)			(0.005)
Observations	28	137	-	27	30	-

Notes: Columns (1) and (2) show the means of each variable conditional on treatment status. Columns (4) and (5) show the re-weighed means such that treated and control slums receive weights 1/p and 1/(1-p) respectively. Columns (3) shows the estimated coefficient of an OLS regression of each variable on treatment. Columns (6) repeats the regression in Column (3), but re-weighing according to (4) and (5).

6.3 Results

Table 3 shows results using the Difference-in-Differences model with IPW for private slums. This sample considers only observations within 4 kilometers of the urban intervention's border.

The estimated effect of higher land value on the probability of slum fire following *Água Espraiada* is both positive and significant. Moreover, estimates are fairly stable after the inclusion of both slum and year fixed effects. They are also robust to adding the interaction of year fixed effects with covariates.[23]

Table 3: Effect of Urban Intervention on Strategic Arson in Slums occupying Private Lands

Dependent Variable:	Probability of Fire			
Model:	(1)	(2)	(3)	(4)
(Intercept)	0.07** (0.04)			
Inside OUC	-0.06* (0.04)			
Year $\geq$ 2005	-0.02 (0.02)	-0.02 (0.02)		
Inside OUC $\times$ Year $\geq$ 2005	0.06*** (0.02)	0.06*** (0.02)	0.06** (0.02)	0.05*** (0.02)
Slum FE (57)		Yes	Yes	Yes
Year FE (15)			Yes	Yes
IPW Covariates * Year				Yes
Observations	855	855	855	855
R^2	0.007	0.339	0.353	0.516
Within R^2		0.006	0.006	0.257

Notes: Slums inside or within 4km of Urban Intervention. Inverse Propensity Score Weighing (IPW) applied to all specifications such that treated units receive 1/p weights whereas control ones receive 1/(1-p) weights.Column (1) has no controls. Column (2) adds slum fixed effects; Column (3) adds year fixed effects; Column (4) adds interactions between IPW covariates and year fixed effects. All errors are clustered at slum level. *p<.1; **p<.05; ***p<.01

These findings are in line with the cross-sectional approach. The estimated increase in land value for exposed slums after the urban intervention is sufficient to move slums from the 9^{th} to the 10^{th} decile of the land value distribution.[24] Therefore, slum land value inside the intervention zone would be crossing the threshold that makes strategic arson

[23] These are the same covariates as the ones included in the propensity score estimation. Covariate levels are fixed to pre-treatment period.

[24] Considering the sample of slums within four kilometers of *Água Espraiada*.

profitable for landowners, thus leading to a sharp increase in slum fires.

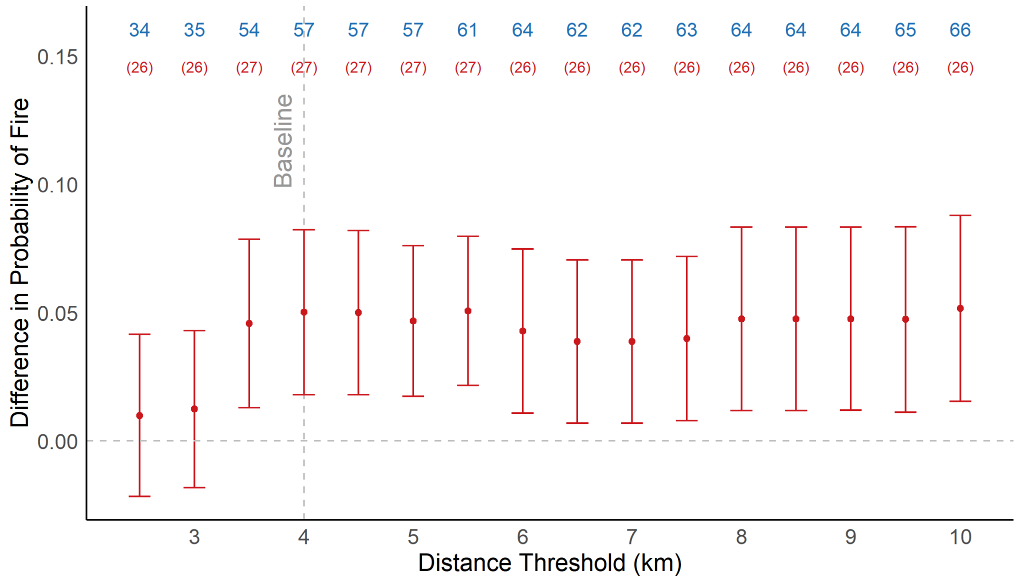
In terms of point-wise estimates, the cross-sectional model suggests that slums going from 9^{th} to 10^{th} decile should experience an 80% increase in the probability of arson, which is quite close to the 70% increase observed in the Difference-in-Differences.

Together with the cross-sectional analysis, Difference-in-Differences results corroborate the theoretical prediction of a non-linear distribution of arson with respect to land value. Combined, these findings suggest that strategic arson associated with urban land conflicts may be happening in this context.

To address concerns with potential pre-trends in the probability of fire prior to the urban intervention, I estimate dynamic effects. Although I cannot get precise estimates for yearly effects due to lack of variation, Appendix Figure E.2 shows no evidence of pre-trends when aggregating the effects for every two years.

One might also be concerned with limiting the distance threshold to four kilometers around the urban intervention. Figure 13 shows that changing this parameter does not seem to affect estimates substantially. The exceptions are the first two categories (2.5 and 3 kilometers), which provide weaker estimates. This is caused by a rather small number of slums outside the intervention area in these cases. There are only 8 and 9 control slums in the 2.5km and 3km thresholds compared with more than 25 for all other thresholds. Therefore, with a reasonably sized control group, estimates seem to be quite robust.

Figure 13: Effect on Probability of Fire for each Maximum Distance Threshold - Private Slums



Notes: The number of total observations for each threshold are in blue, whereas the number of treated units are in red and in brackets. Treated units are all slums inside the perimeter of the urban intervention. Control units are all slums located further than 500 meters from the urban intervention and within each distance threshold. Units with estimated propensity score higher than 0.95 or lower than 0.05 were discarded.

Table E.1 and Figure E.3 in the Appendix replicate the results above for the unmatched sample of private slums. Overall, conclusions are similar, although estimates get weaker for higher distance thresholds. This is likely related with the fact that slums closer to the intervention area are not necessarily comparable with those that are much further away.

Additionally, there is the issue of different geocoding success rates for slum fires throughout the sample period, which was mentioned Section 4. To account for this, apart from including year fixed effects, I also test multiple sub-samples in Appendix E, restricting the analysis to shorter periods. Using specifications from Columns (4) and (8) in Table 3, I show that estimates are fairly robust even when I limit the sample to years ranging from 2001 to 2006, which avoids mixing the different cycles of data described in Figure 3 of Section 4. This exercise is detailed in Appendix Table E.2.

Another concern is that confounding factors could be driving both density and slum fires inside the intervention zone. However, when estimating the same model for public slums, we do not find similar results. Table 4 shows no effect of the intervention when comparing slums inside and outside its perimeter. This is also robust to different distance thresholds, as illustrated by Appendix Figure E.4.

Table 4: Effect of Urban Intervention on Strategic Arson in Slums occupying Public Lands

Dependent Variable:	Probability of Fire			
Model:	(1)	(2)	(3)	(4)
(Intercept)	0.01* (0.008)			
Inside OUC	0.02 (0.03)			
Year $\geq$ 2005	0.008 (0.008)	0.008 (0.008)		
Inside OUC $\times$ Year $\geq$ 2005	-0.02 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)
Slum FE (93)		Yes	Yes	Yes
Year FE (15)			Yes	Yes
IPW Covariates * Year				Yes
Observations	1,395	1,395	1,395	1,395
R^2	0.001	0.190	0.201	0.375
Within R^2		0.001	0.001	0.218

Notes: Slums inside or within 4km of Urban Intervention. Inverse Propensity Score Weighing (IPW) applied to all specifications such that treated units receive 1/p weights whereas control ones receive 1/(1-p) weights.Columns (1) has no controls. Column (2) adds slum fixed effects; Column (3) adds year fixed effects; Column (4) adds interactions between IPW covariates and year fixed effects. All errors are clustered at slum level. *p<.1; **p<.05; ***p<.01

Finding positive and significant estimates only for private slums provides further evidence in favor of strategic arson, because this highlights the importance of property rights in the allocation of fires. If fires were simply related to infrastructure or density in slums, we should observe similar results for private and public lands — both in the cross-sectional and Difference-in-Differences approaches.

7 Conclusion

In this paper, I investigate whether land conflicts also happen in the urban context, but rather in a different form. Instead of open confrontation between armed groups, I study arson as one violent outcome of these conflicts.

To overcome challenges such as measurement error and confounding factors, I provide two empirical exercises: a panel model regression controlling for observables and a Difference-in-Differences. In both cases, I show evidence that fires are abnormally more likely to happen in slums with high land value. This effect is exclusive for slums in private lands and it does not seem to be driven by accidental fires. Moreover, conclusions from both approaches are in line with each other and support predictions from the theoretical model. The urban intervention I explore in the Difference-in-Differences seems to have moved slum land value across the threshold implied by cross-sectional estimates.

Such findings corroborate the hypothesis that arson might be a violent tool in urban land conflict. These results also highlight the importance of addressing the lack of land property rights in slums. As is the case in rural areas, disputes between residents and landowners can escalate to violence if enforcement of land property rights is imperfect.

To compensate for this, governments could take a more active role in increasing the cost of violence, pushing to improve slums' infrastructure and land ownership status. Moreover, part of this issue could also be mitigated by policies that reduce the creation of new slums.

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APPENDIX

A Theoretical Model

The model focuses on the decision of a landowner who claims ownership for a squatted land plot. I assume that a repossession claim is already running in court and she is now waiting for a decision, which could take years. Uncertainty about the timing of a court ruling, combined with increasing land value, poses a dynamic trade-off to the landowner: she can either wait another period for a court decision; or she can cause the slum to burn, anticipating the conclusion of the dispute. By doing this, she either gains control over the land or goes to prison with some probability.

This theoretical approach is analogous to Capozza and Sick (1994), who study a landowners' decision of when to develop an empty land plot depending on housing prices. The intuition is that starting the construction of a building, if irreversible, works as a real option. As such, there is an optimal timing to start the construction. If rent is cheap, the landowner prefers to maintain the land undeveloped, earning some agricultural income. However, if expected profits from renting future housing or commercial units is high enough, the landowner chooses to incur the development costs and thus renounce the agricultural rent. The fundamental insight from the this problem is that there is an optimal price above which developing the land is better than doing nothing.

Different from Capozza and Sick (1994), however, the decision to burn a slum bears some additional subtleties. First, not only does it depend on the value of a reclaimed land plot, but also on how likely the court is to provide a final decision on the matter. Second, it also hinges on how likely the decision is to favor the landowner. Third, it depends on the moral and financial costs of committing arson, as well as on the probability of destroying the slum with it. Finally, waiting for courts entail a judicial cost, such as lawyers' hourly rates for example.

More formally, the agent is faced with a maximization problem represented by the following value function $w(\cdot)$:

$$w(R_{it}) = max\{u(R_{it}); -c(1-\delta) + \delta E_R[\lambda\theta\Delta v(R_{i,t+1}) + (1-\lambda\Delta)w(R_{i,t+1})]\} \tag{A.1}$$

Such that $R_{it} = log(p_{it})$ and p_{it} is the real estate price of slum i in year t; Δ is the length of the discrete time interval (i.e. one year); and $\delta = e^{r\Delta}$ represents the discount factor for a given length of the time interval Δ. Moreover, E_R is an expected value and it depends on the realization of the stochastic quantity R_{it}.

If the agent decides to burn the slum, this is irreversible and she gets u_{it}. Alternatively, if she decides to wait, she pays a cost c to keep pushing her claim in court. In the following period $t+1$, courts issue a decision with probability λ. In this case, she gains control over the land with probability θ and gets a payoff of $v(R_{i,t+1})$. With probability $(1-\lambda)$, courts delay their ruling, and the agent repeats her decision in the next period. This postponement is represented by the value function in $t+1$, i.e. $w(R_(i,t+1))$, which means that the agent will confront the same maximization problem in the future.

In summary, in every period, the landowner chooses whichever is higher between the present payoff of burning the slum and the expected payoff of waiting for a court ruling. This ultimately hinges on how high the real estate value p_{it} is for the occupied land. As one may anticipate, this problem yields an optimal threshold p^*, above which it is more profitable for landowners to burn the slum.

I assume a standard dynamics for the real estate prices (Capozza and Li, 1994; Capozza and Sick, 1994). Returns to real estate investment dR follows a Brownian Motion with mean growth rate μ, standard deviation σ and with shocks dz from a standard Wiener process, i.e.[25]

$$dR = \mu\Delta + \sigma dz \tag{A.2}$$

$$z \sim N(0,1) \tag{A.3}$$

To find a closed-form solution, it is more convenient to work with continuous time. To go from a discrete to a continuous model, I make $\Delta \to 0$ and combine A.1 with A.2. This yields the following second-order differential equation for the continuation region (when the agent decides to wait), analogously to Capozza and Li (1994); Capozza and Sick (1994):

$$(\lambda + r)w(R) = -rc + \lambda\theta v(R) + \mu w'(R) + \frac{1}{2}\sigma^2 w''(R) \tag{A.4}$$

Such that r is a continuous discount factor.

The solution to this problem is characterized not only by the unique value function $w(\cdot)$, but also by the threshold R^*, which in turn defines a p^* that separates the decision to *burn* the slum from the one to *wait* for a court ruling. I find these two quantities by resorting to classical conditions presented in Dixit and Pindyck (1994):

1. **No Dynamics:** when $R \to -\infty$ (or $p \to 0$). In this case, the path of prices over time

[25] Notice that $dR = \frac{dP}{P}$, the return on a real estate asset with price P.

does not matter anymore. In all time periods, the agent sticks to either *burning* or *waiting* — whichever provides higher utility:

$$w(-\infty) = max\left\{\frac{-rc + \lambda\theta v(-\infty)}{\lambda + r}; u(-\infty)\right\} \tag{A.5}$$

2. **Value Matching:** the utility of *waiting* and *burning* must be the same in threshold point R^*.

$$w(R^*) = u(R^*) \tag{A.6}$$

3. **Smooth Pasting:** intuitively, this condition can be thought of as a maximization problem in which, given the value function, the agent chooses the threshold R^* that gives her the highest utility.

$$w'(R^*) = u'(R^*) \tag{A.7}$$

Furthermore, for a solution to exist, the distance between the payoffs of *burning* and *waiting* must decrease with prices. Otherwise, the agent would never decide to burn if she started in the waiting region. Formally, this means the following expression must be increasing in R:

$$u(R) - (\lambda + r)w(R) + rc - \lambda\theta v(R) - \mu w'(R) - \frac{1}{2}\sigma^2 w''(R) \tag{A.8}$$

Still seeking to provide a closed-form solution, I also define functional forms for $v(R)$ and $u(R)$. I resort again to an optimal stopping framework such that $v(R)$ is the solution to the problem of a landowner who decides when to develop an empty plot (Capozza and Sick, 1994; Capozza and Li, 1994). I assume no operating costs to maintain the plot undeveloped and the same discrete discount rate, δ.

In this follow-up decision, the landowner gets the discounted future payoffs represented by $v(R')$ if she decides not to develop the land plot, which is the value function in the next period. Alternatively, if she decides to develop the plot, she gets a payoff equal to real estate value e^R minus investment cost I. Formally,

$$v(R) = max\{e^R - I; \delta v(R')\} \tag{A.9}$$

Under similar conditions as in the previous problem, the solution is characterized by a unique value function $v(\cdot)$ and threshold R^*, above which the landowner chooses to develop the plot. Assuming returns maintain the same stochastic process as before, I solve the following homogeneous second order differential equation:

$$\frac{1}{2}\sigma^2 v''(w) + gv'(R) - rv(R) = 0 \tag{A.10}$$

subject to analogous conditions:

1. **No Dynamics:** $v(-\infty) = 0$

2. **Value Matching:** $v(\hat{R}) = e^{\hat{R}} - I$

3. **Smooth Pasting:** $v'(\hat{R}) = e^{\hat{R}}$

Assuming that $e^R - I - \frac{1}{2}\sigma^2 v''(R) - gv'(R) + rv(R)$ is increasing in R, I find

$$v(R) = \frac{I}{\alpha - 1} e^{(R-\hat{R})\alpha} \tag{A.11}$$

Such that the positive root of the polynomial is given by

$$\alpha = \frac{1}{\sigma}\left[-\frac{\mu}{\sigma} + \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right] \tag{A.12}$$

and the optimal threshold in the land-development problem is given by

$$\hat{R} = log\left[\frac{\alpha I}{\alpha - 1}\right] \tag{A.13}$$

Now, I define a functional form for $u(R)$, the utility in case of *burning*. Assuming the new landowner wishes to eventually develop the plot after the slum is destroyed, I assume the payoff is similar to $v(R)$, but with an additional fixed cost k for burning the slum. Moreover, there is a probability β that the agent will go to jail for committing arson, getting no benefits from the removal. Formally,

$$u(R) = (1 - \beta)v(R) - k \tag{A.14}$$

We can solve Equation A.4 by plugging Equations A.11 and A.14, using conditions

A.5 through A.8. After some algebra, we get

$$w(R) = e^{(R-R^*)\gamma}\left[\frac{rc}{\lambda+r} + (1-\theta-\beta)\frac{Ie^{(R^*-\hat{R})\alpha}}{\alpha-1} - k\right] - \frac{rc}{\lambda+r} + \frac{\theta I}{\alpha-1}e^{(R-\hat{R})}\alpha \tag{A.15}$$

In which γ is the positive root of the differential equation in A.4

$$\gamma = \frac{1}{\sigma}\left[-\frac{\mu}{\sigma} + \sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)}\right] \tag{A.16}$$

And

$$R^* = \hat{R} + \frac{1}{\alpha}log\left[\frac{\gamma(\alpha-1)}{I(1-\theta-\beta)(\gamma-\alpha)}\left(k - \frac{rc}{\lambda+r}\right)\right] \tag{A.17}$$

Finally, plugging $R = log(p)$ yields an expression in terms of real estate value instead of returns:

$$p^* = \hat{p}\left[\frac{\gamma(\alpha-1)}{I(1-\theta-\beta)(\gamma-\alpha)}\left(k - \frac{rc}{\lambda+r}\right)\right]^{\frac{1}{\alpha}} \tag{A.18}$$

Before moving to the implications of Equation A.18, there are two remarks about parameters. First, using A.8 one can show that $k > \frac{rc}{\lambda+r}$. This means that, at least in terms of costs, the agents prefer using the legal system instead of burning a slum. Second, for the solutions presented here to be well-defined, one needs $\theta + \beta < 1$. This means that the probability of going to jail because of arson plus the probability of winning a lawsuit cannot be too high.

The last step is to find how the probability of arson responds to an increase in the slum's real estate price. Since the agent burns the slum whenever $p \geq p^*$, the probability of observing arson as a function of the slum's real estate value is given by

$$P(arson) = P(p \geq p^*) \tag{A.19}$$

$$= P\left\{p \geq \hat{p}\left[\frac{\gamma(\alpha-1)}{I(1-\theta-\beta)(\gamma-\alpha)}\left(k - \frac{rc}{\lambda+r}\right)\right]^{\frac{1}{\alpha}}\right\} \tag{A.20}$$

Let us also assume that the cost of burning a slum is not the same for all potential arsonists, but instead follows a generic distribution such as

$$k = \tilde{k} \sim F(\cdot) \tag{A.21}$$

Then, isolating $\tilde{k}$ and re-writing Equation A.19 gives

$$P(arson) = P\left\{\tilde{k} \leq \left[\frac{p}{\hat{p}}\right]^{\alpha}\left[\frac{I(1-\theta-\beta)(\gamma-\alpha)}{\gamma(\alpha-1)}\right] + \frac{rc}{\lambda+r}\right\} \tag{A.22}$$

$$= F\left(\left[\frac{p}{\hat{p}}\right]^{\alpha}\left[\frac{I(1-\theta-\beta)(\gamma-\alpha)}{\gamma(\alpha-1)}\right] + \frac{rc}{\lambda+r}\right) \tag{A.23}$$

Differentiating this probability with respect to p and defining $F'(\cdot) = f(\cdot) > 0$ as the probability density function then yields

$$\frac{\partial P(arson)}{\partial p} = f\left(\left[\frac{p}{\hat{p}}\right]^{\alpha}\left[\frac{I(1-\theta-\beta)(\gamma-\alpha)}{\gamma(\alpha-1)}\right] + \frac{rc}{\lambda+r}\right) * \tag{A.24}$$

$$* \, \alpha \left[\frac{p}{\hat{p}}\right]^{\alpha-1}\left[\frac{I(1-\theta-\beta)(\gamma-\alpha)}{\gamma(\alpha-1)}\right] \tag{A.25}$$

Since $\theta - \beta < 1$ and $\alpha > 1$ for $\hat{R}$ to be well-defined in Equation A.13, demonstrating that $\gamma - \alpha > 0$ implies that this derivative is positive. I do this by plugging the actual values of polynomial roots from Equations A.12 and A.26 and simplifying the resulting expression:

$$\gamma - \alpha = \frac{1}{\sigma}\left[-\frac{\mu}{\sigma} + \sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)}\right] - \frac{1}{\sigma}\left[-\frac{\mu}{\sigma} + \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right] \tag{A.26}$$

$$= \frac{1}{\sigma}\left[\sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)} - \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right] \tag{A.27}$$

$$= \frac{1}{\sigma}\left[\sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)} - \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right] * \frac{\left[\sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)} + \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right]}{\left[\sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)} + \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right]} \tag{A.28}$$

$$= \frac{2\lambda}{\left[\sqrt{\frac{\mu^2}{\sigma^2} + 2(\lambda+r)} + \sqrt{\frac{\mu^2}{\sigma^2} + 2r}\right]} > 0 \tag{A.29}$$

Hence, increasing the real estate value of a slum leads to a higher probability of strategic arson against it.

B Anecdotal Evidence from News Pieces

The following list contains some cases of fires being associated to slum removal episodes in high-value neighborhoods, both in Brazil and other countries.

1. Fire during removal in Praia do Pinto (Rio de Janeiro, RJ) – 1969
   http://www.encontro2012.historiaoral.org.br/resources/anais/3/1339790201_ARQUIVO_MemoriasdaRemocaoABHO2012.pdf

2. Fire in Ocupacao Nelson Mandela (Osasco, SP) – 2015
   https://sao-paulo.estadao.com.br/noticias/geral,moradores-ateiam-fogo-em-barracos-durante-reintegracao-de-posse-em-sp,1702643

3. Fire in Favela Estaiadinha (Sao Paulo, SP) – 2011
   http://g1.globo.com/sao-paulo/noticia/2011/09/moradores-sao-retirados-de-favela-durante-reintegracao-de-posse-em-sp.html

4. Fire in Favela Real Parque (Sao Paulo, SP) – 1992, 2010
   https://rollingstone.uol.com.br/edicao/56/arquitetura-da-destruicao/

5. Fire in Favela Buraco Quente (Sao Paulo, SP) – 2004, 2012, 2014
   https://www.redebrasilatual.com.br/cidadania/2014/09/incendio-na-favela-do-buraco-quente-terminou-o-servico-de-alckmin-contra-moradores-7676.html

6. Fire in Ocupacao Esperanca (Osasco, SP) – 2016
   http://agenciabrasil.ebc.com.br/geral/noticia/2016-09/incendio-em-area-desapropriada-causa-estranheza-em-prefeito-de-osasco

7. Fire in New Delhi, India – 2018
   https://www.theguardian.com/cities/2018/sep/05/devastated-destroyed-delhi-slums-recover-fires

8. Fire in Dhaka, Bangladesh – 2016
   https://archive.dhakatribune.com/bangladesh/2016/12/24/dhaka-slum-fires-arson

9. Fire in Favela do Piolho (Sao Paulo, SP) – 2014
   https://sao-paulo.estadao.com.br/noticias/geral,bombeiros-acreditam-que-incendio-em-favela-de-sp-foi-criminoso,1556959

10. Fire in Favela do Cimento (Sao Paulo, SP) – 2019
   https://www1.folha.uol.com.br/cotidiano/2019/03/incendio-toma-conta-de-favela-na-radial-leste-que-seria-desocupada.shtml
   https://g1.globo.com/sp/sao-paulo/noticia/2019/03/25/policia-prende-suspeito-de-iniciar-fogo-que-destruiu-a-favela-do-cimento-no-entorno-do-viaduto-bresser.ghtml

11. Fire in Favela 21 de Abril (Sao Paulo, SP) – 2014
   http://g1.globo.com/bom-dia-brasil/noticia/2014/10/um-em-cada-quatro-incendios-em-favelas-de-sao-paulo-e-criminoso.html

C Aggregating Property Tax Data around Slums

In the main text, the formula for calculating the land value proxy assumes data is available for each property i individually. One limitation, however, is that I observe properties at the street section level, each of which has roughly 200 meters. This adds an additional step to calculations, since I must compute an average quantity for each street section and then calculate $SlumValue^r_{st}$ by averaging streets at a given distance r from slum s.

When calculating average values within a given radius of slum borders, I account for the fact that some street segments are partially outside of these buffer areas. Ignoring this feature could be a potential problem for street segments that are too long, but still intersect with the buffer region around slums. Since properties further from slums tend to have higher values, this could overestimate $SlumValue_{st}$.

To avoid this, I calculate the proportion of each segment that lies inside the buffer region and use these shares as weights when calculating $SlumValue_{st}$. This decreases the influence of segments that are predominantly outside the pre-defined radius. Formally, proxies for slum land value using data within distance r of slum s in year t are given by

$$SlumValue^r_{st} = \frac{\sum_{i=1}^{I} sh\_length(i,s,r) * TotalNumerator_{it}}{\sum_{i=1}^{I} sh\_length(i,s,r) * TotalDenominator_{it}} \tag{C.1}$$

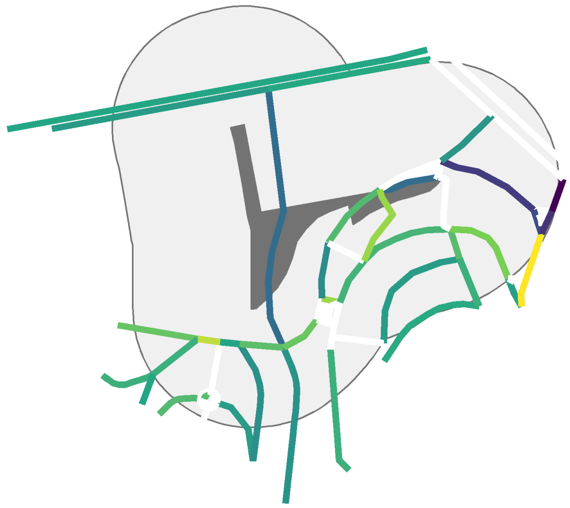
Such that $TotalNumerator_{it}$ and $TotalDenominator_{it}$ are, respectively, the total built area and the total plot area in each street segment.

Moreover, $sh\_length(i,s,r)$ is the length of segment i that lies inside the buffer region with radius r around slum s divided by its total length, or

$$sh\_length(i,s,r) = \frac{length(i,s,r)}{length_i} \tag{C.2}$$

To illustrate this, Figure C.1 shows street segments, the 500-meter buffer area, and average segment values for a slum in the sample.

Figure C.1: Example of street segments around slum with 500-meter buffer in 2011



Notes: This figures shows a slum (dark grey) and a buffer area with a 500-meter radius (light grey). Street segments are colored from lower (darker colors) to higher (lighter colors) proxy values. Streets segments in blank (white) had no properties found in tax data.

D Propensity Score Estimation

Tables D.1 and D.2 present the estimated propensity score models for private and public slum-occupied land, respectively, and a maximum distance threshold of 4 kilometers.

The following variables are from the 2000 Census: *Share Water*, *Share Bathroom*, *Share Trash Collection*, *Share Income up to 3 Salários Mínimos*, *Residents per Household*, *Households per Hectare*. The following variables are from 1995 property tax data: *(log) Neighborhood F.A.R.* and *(log) Property Value*. *Slum Area* and *Share Landslide Risk* are geographical features from municipal government data for slums that existed in 2000.

Table D.1: Probit Regression of Probability that Slum is inside Urban Intervention on Pre-Treatment Characteristics - Private Slums within 4 kilometers

Share Water	8.32 (14.65)
Share Bathroom	−0.35 (18.81)
Share Trash Collection	−4.69 (7.82)
Share Income up to 3 Salarios Minimos	3.04 (1.91)
Residents per Household	0.54 (0.76)
Households per hectare	−0.0001 (0.0001)
(log) Neighborhood F.A.R.	3.43** (1.39)
(log) Neighborhood Property Value	−0.58 (1.08)
(log) Slum Area	0.03 (0.22)
Share Landslide Risk	−5.00* (2.57)
Constant	−2.56 (10.37)
Pseudo-R2	0.43
AIC	107.22
Observations	165

Notes: Slums inside and within 4km of Urban Intervention's border. *p<.1; **p<.05; ***p<.01

Table D.2: Probit Regression of Probability that Slum is inside Urban Intervention on Pre-Treatment Characteristics - Public Slums within 4 kilometers

Share Water	0.40 (1.88)
Share Bathroom	-11.65^{*} (6.26)
Share Trash Collection	0.43 (5.69)
Share Income up to 3 Salarios Minimos	3.06^{**} (1.37)
Residents per Household	1.25^{**} (0.55)
Households per hectare	-0.0001 (0.0001)
(log) Neighborhood F.A.R.	2.03^{**} (0.83)
(log) Neighborhood Property Value	1.06^{*} (0.55)
(log) Slum Area	-0.48^{**} (0.19)
Share Landslide Risk	-1.15 (0.74)
Constant	-0.62 (4.24)
Pseudo-R2	0.45
AIC	143.34
Observations	329

Notes: Slums inside and within 4km of Urban Intervention's border. *p<.1; **p<.05; ***p<.01

Table D.3 shows balance in observables for public slums and distance threshold of 4 kilometers.

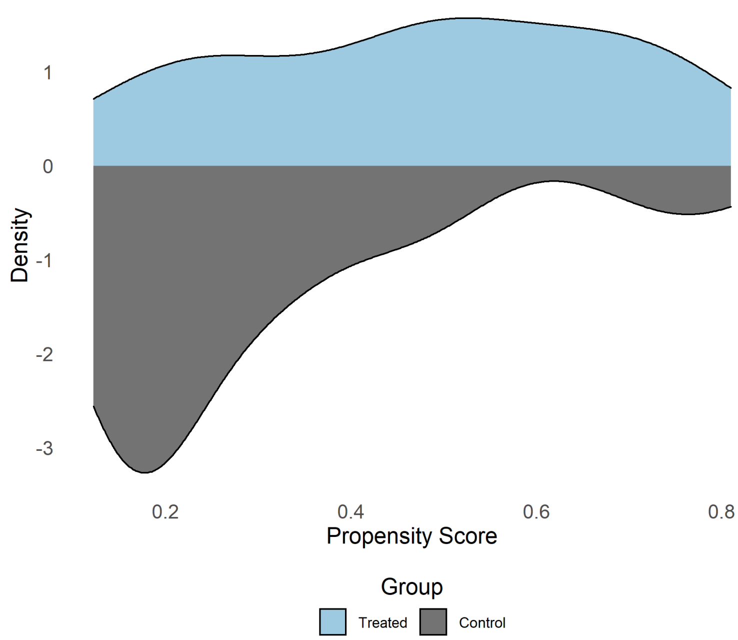
Figures D.1 and D.2 provide evidence of common support for treated and control units among private and public slums respectively.

Table D.3: Propensity-Score Matching Balance Test for Slums in Public Land inside or within 4km of Urban Intervention

	Unmatched			Matched		
	Treated	Control	Difference	Treated	Control	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Households per hectare	1783.809	1988.811	-205.002	1794.945	1739.22	55.725
			(929.946)			(414.214)
(log) Slum Area	-1.466	-1.014	-0.452	-1.397	-1.455	0.059
			(0.248)			(0.236)
(log) Neighborhood F.A.R.	-0.34	-0.815	0.475	-0.458	-0.401	-0.057
			(0.067)			(0.047)
(log) Neighborhood Property Value	5.091	4.454	0.637	4.826	4.973	-0.146
			(0.079)			(0.077)
Residents per Household	3.738	3.701	0.037	3.697	3.662	0.035
			(0.049)			(0.058)
Share Bathroom	0.966	0.986	-0.02	0.98	0.973	0.007
			(0.007)			(0.01)
Share Income up to 3 Salarios Minimos	0.375	0.386	-0.012	0.349	0.348	0.001
			(0.022)			(0.027)
Share Landslide Risk	0.048	0.219	-0.171	0.127	0.063	0.064
			(0.054)			(0.044)
Share Trash Collection	0.964	0.981	-0.017	0.977	0.971	0.006
			(0.008)			(0.01)
Share Water	0.918	0.983	-0.065	0.98	0.966	0.014
			(0.013)			(0.011)
Observations	34	295	-	23	70	-

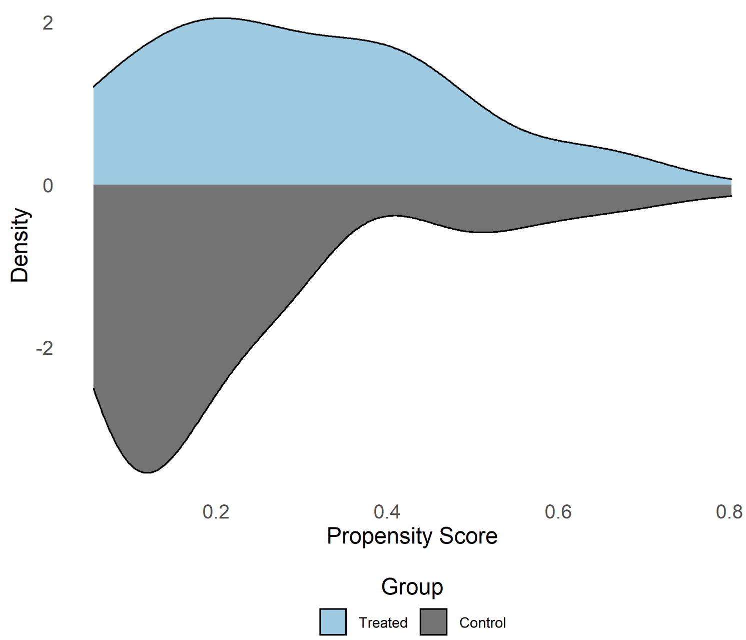
Notes: Columns (1) and (2) show the means of each variable conditional on treatment status. Columns (4) and (5) show the re-weighed means such that treated and control slums receive weights 1/p and 1/(1-p) respectively. Columns (3) shows the estimated coefficient of an OLS regression of each variable on treatment. Columns (6) repeats the regression in Column (3), but re-weighing according to (4) and (5).

Figure D.1: Distribution of Propensity Scores for Treated and Control Units - Private Slums within 4 kilometers of Agua Espraiada



Notes: Treated units are all slums inside the perimeter of the urban intervention. Control units are all slums located both further than 500 meters and within 4 kilometers of the urban intervention. Units with estimated propensity score higher than 0.95 or lower than 0.05 were discarded.

Figure D.2: Distribution of Propensity Scores for Treated and Control Units - Public Slums within 4 kilometers of Agua Espraiada



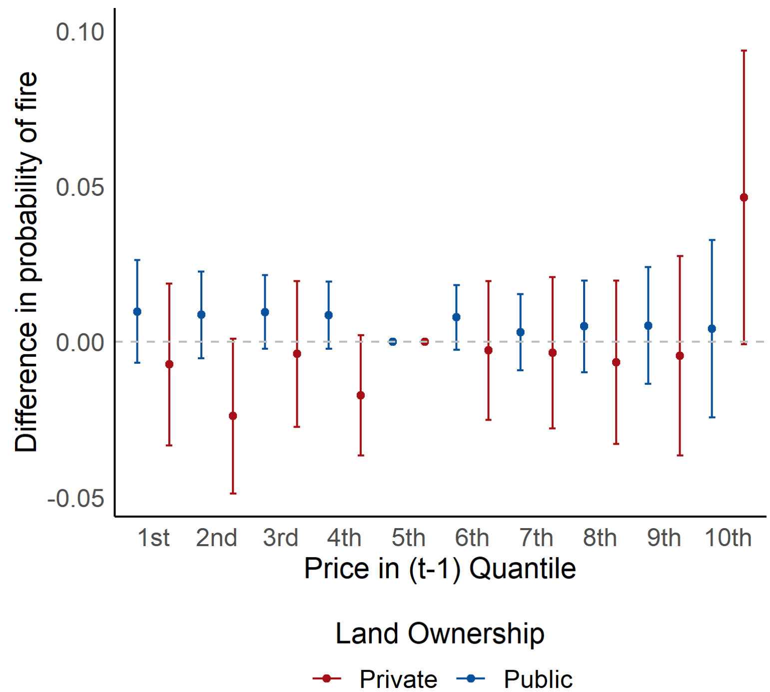
Notes: Treated units are all slums inside the perimeter of the urban intervention. Control units are all slums located both further than 500 meters and within 4 kilometers of the urban intervention. Units with estimated propensity score higher than 0.95 or lower than 0.05 were discarded.

E Additional Results and Robustness Checks

E.1 Panel Regression

Figure E.1 presents results for a panel regression using quantiles of assessed property value per square meter instead of floor-to-area ratio. Moreover, I use prices in $t-1$ to avoid simultaneity bias.

Figure E.1: Difference in Probability of Fire for Slums in either Private or Public Land

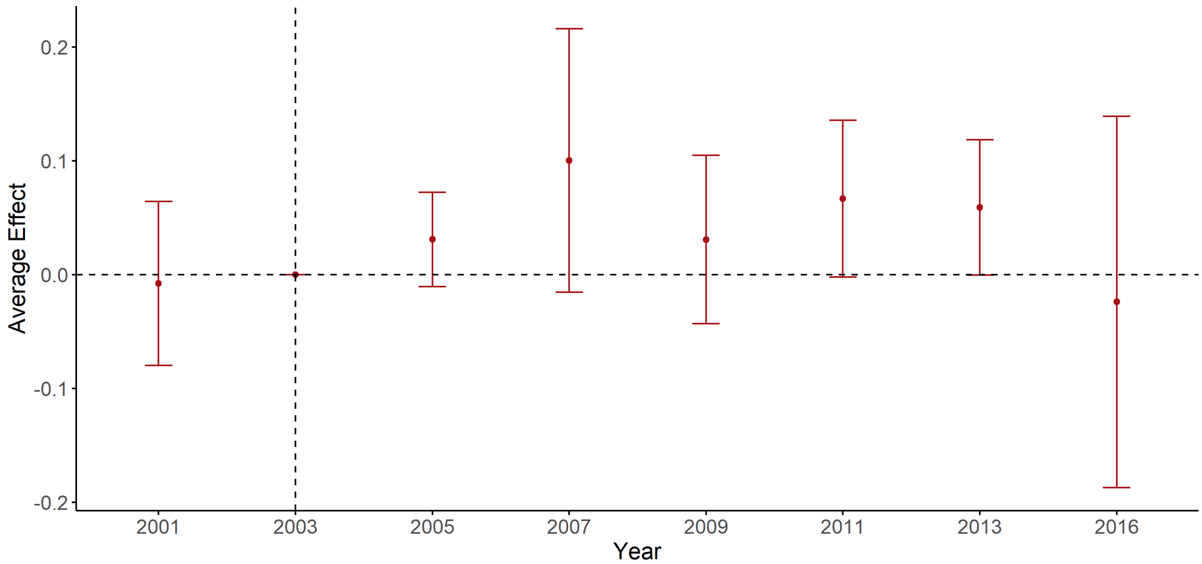


The pointwise estimate for private slums in the highest quantile is similar to that of the main result in Figure 7b, but standard errors are larger. At a 10% significance level, the conclusion is the same as before: slums in relatively more expensive neighborhoods are subject to an abnormally higher probability of fire.

E.2 Difference-in-Differences

Figure E.2 presents an event study form of the main Difference-in-Differences specification. Results are aggregated for every two years, since there is not enough variation to estimate coefficients for all years separately. There does not seem to be any evidence of pre-trends prior to the urban intervention, and the probability of fire seems to increase after the shock in slum land value.

Figure E.2: Effect on Probability of Fire for every Two Years - Private Slums



Notes: Due to little variation in some years, this figure presents the estimated difference between exposed and non-exposed slums estimated for every two years. The years presented in the horizontal axis correspond to the first one of the pair. The coefficient for 2016 is estimated separately, because the number of years is odd.

Table E.1 presents results for the unmatched Difference-in-Differences, i.e., without using IPW or restricting the sample according to propensity score estimates. Results are similar to the re-weighed model once I control for all covariates and fixed effects. This suggests that the inclusion of observable characteristics, either explicitly or via IPW, helps smoothing potential pre-treatment differences across treated and control units.

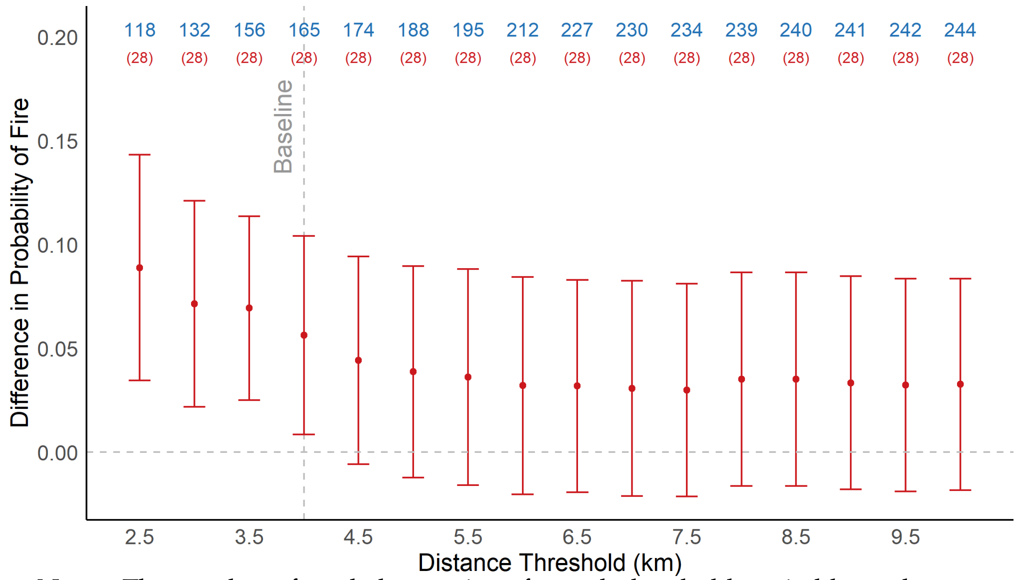
Table E.1: Effect of Urban Intervention on Strategic Arson in Slums occupying Private Lands

Dependent Variable:	Probability of Fire			
Model:	(1)	(2)	(3)	(4)
Inside OUC	0.02			
	(0.04)			
Year $\geq$ 2005	-0.002	-0.002		
	(0.007)	(0.007)		
Inside OUC $\times$ Year $\geq$ 2005	0.03	0.03	0.03	0.06^{**}
	(0.03)	(0.03)	(0.03)	(0.02)
Slum FE (165)		Yes	Yes	Yes
Year FE (15)			Yes	Yes
Covariates * Year				Yes
Observations	2,475	2,475	2,475	2,475
R^2	0.007	0.293	0.296	0.348
Within R^2		0.001	0.001	0.075

Notes: Slums inside or within 4km of Urban Intervention. Columns (1)-(4) report effects on probability of fire. Column (1) has no controls. Column (2) adds slum fixed effects; Column (3) adds year fixed effects; Column (4) adds interaction between covariates and year fixed effects. All errors are clustered at slum level. *p<.1; **p<.05; ***p<.01

In Figure E.3, we see that results depend more on the maximum distance threshold in the absence of IPW. This is likely attributable to the fact that slums further apart might be, on average, less comparable to the treated group.

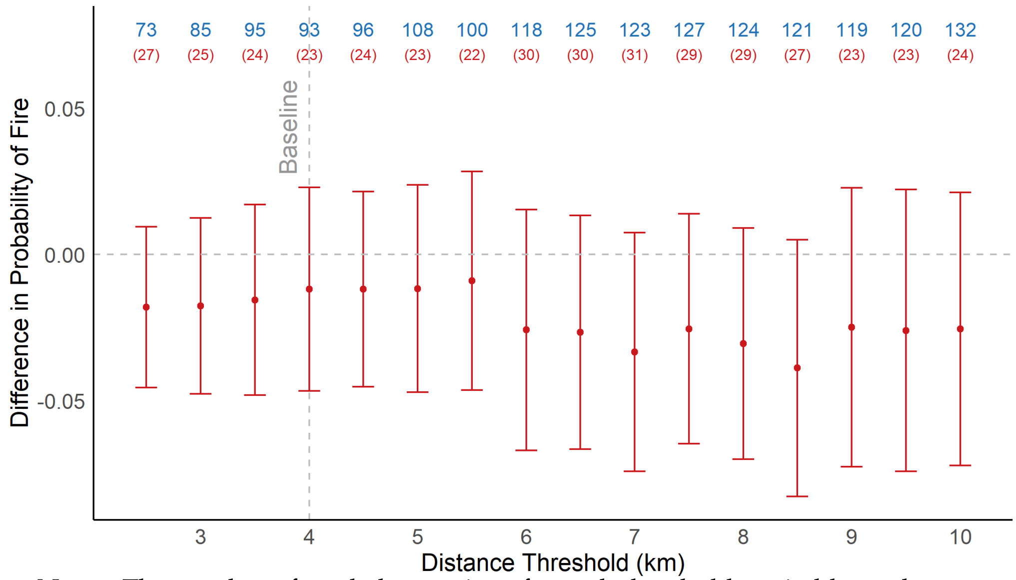
Figure E.3: Effect on Probability of Fire for each Maximum Distance Threshold - Unmatched Sample of Private Slums



Notes: The number of total observations for each threshold are in blue, whereas the number of treated units are in red and in brackets. Treated units are all slums inside the perimeter of the urban intervention. Control units are all slums located further than 500 meters from the urban intervention and within each distance threshold.

Figure E.4 provides a sensitivity analysis for slums in public lands, with all controls and IPW. For a wide range of possible thresholds, there is no evidence of strategic arson in public lands.

Figure E.4: Effect on Probability of Fire for each Maximum Distance Threshold - Public Slums



Notes: The number of total observations for each threshold are in blue, whereas the number of treated units are in red and in brackets. Treated units are all slums inside the perimeter of the urban intervention. Control units are all slums located further than 500 meters from the urban intervention and within each distance threshold. Units with estimated propensity score higher than 0.95 or lower than 0.05 were discarded.

In the following table, I re-estimate the main specification, but now restricting the sample to different periods. For each column, the header indicates first and last years of sample. For example, in Column (1) from Table E.2, I estimate the model for years ranging from 2001 to 2016 (full sample). In Column (2), the sample goes from 2001 to 2015. In (3), from 2001 to 2014. And so on and so forth.

Table E.2: Effect of Urban Intervention on Probability of Fire in Slums occupying Private Lands - Alternative Sample Periods

Dependent Variable:	Probability of Fire									
Sample Period:	2001-2016	2001-2015	2001-2014	2001-2013	2001-2012	2001-2011	2001-2010	2001-2009	2001-2008	2001-2006
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inside OUC $\times$ Year $\geq$ 2005	0.05^{***}	0.06^{***}	0.06^{***}	0.06^{***}	0.06^{***}	0.06^{***}	0.05^{***}	0.06^{***}	0.06^{**}	0.04^{*}
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Slum FE (57)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPW Covariates * Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Year FE	15	14	13	12	11	10	9	8	7	6
Observations	855	798	741	684	627	570	513	456	399	342
R^2	0.516	0.531	0.550	0.554	0.557	0.581	0.627	0.650	0.650	0.693
Within R^2	0.257	0.259	0.276	0.284	0.292	0.308	0.308	0.328	0.321	0.334

Notes: Slums inside or within 4km of Urban Intervention. Inverse Propensity Score Weighing (IPW) applied to all specifications such that treated units receive 1/p weights whereas control ones receive 1/(1-p) weights. Each column header indicates the the sample period. All columns have slum and year fixed effects, as well as interaction between IPW covariates and year fixed effects. All errors are clustered at slum level. *p<.1; **p<.05; ***p<.01