Promoting Social Housing : Insights from Redevelopment Policies in Paris

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Abstract

The issue of income segregation plagues numerous cities, and in particular Paris which is studied here. To mitigate this problem, the local government has implemented redevelopment policies that increase incentives to convert offices and other commercial units into moderate-rent dwellings in high-demand areas. We find that these policies have mixed effects. Only the most restrictive law significantly stimulates the conversion of social housing in the city center at the expense of the periphery, but none of these policies have an impact on social diversity.

JEL Classification: R12, R20, R52.

Key Words: Neighborhoods, Real Estate Demand, Redevelopment Supply, Gentrification

1 Introduction

Income seggregation is a significant problem in many cities in the world leading to unequal access to employment, education, healthcare, and other important resources and opportunities. Housing scarcity in high-demand areas is one of the cause of this social phenomenom, that has for instance led the movement of YIMBY (*Yes In My Back Yard*) in the U.S. to support more private and public housing (Dougherty, 2020).

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In this study, we investigate a range of urban regulations in Paris, where the YIMBY label is not used, but where the arrival in power of a socialist mayor, and its re-election in 2008, was in part driven by the same narrative of ensuring affordable housing in Paris.[1] Indeed, Paris has a long history of concentrating a disproportionately high level of wealth in its center compared to its metropolitan area and the rest of France.[2] To combat this long-term trend, several laws have been voted in the past decade, including rent control[3] and a steady increase in the minimum quota of social housing, hereafter called HLM (*Habitations à Loyer Modéré* which means moderate rent dwellings).[4] Beside these standard policies, the city of Paris has passed in 2009 a new act regarding the conversion of shops and offices (but also warehouses, restaurants, hotels, cinema, etc.[5]) into housing which fosters redevelopment of private housing or of public dwelling. More precisely, three laws have been voted in 2009, 2011 and 2014 under the same principle that one square meter of private housing redeveloped for commercial use should be compensated by the redevelopment of two square meters of commercial unit into private housing. There is however one important exception to this rule, if the conversion goes to the redevelopment of public dwelling (and not private), then the compensated surface should be identical to (only) the initial change (1:1 rule). This offers a distinct economic benefit for the redevelopment of social housing compared to the redevelopment of private housing. Through this channel, the housing composition of Paris may gradually shift, marked by an increased focus on public dwellings. This could potentially lead to a decrease in income-based spatial segregation.

The aim of these laws were to reduce the redevelopment of commercial unit and to increase the supply of social housing in a satured spatial context where construction of new buildings were limited. Did it work?

We find that these three regulations have significantly increased the social housing conversions. However, the subtle differences between these laws have had dif-

[1] The website of the candidate and future mayor, Bertrand Delanoë, is no longer online but can be accessed via waybackmachine. One of its main campaign promise in 2008 was the building of 40,000 additional social housing units in the capital over the period 2008-2014.

[2] According to Piketty et al. (2006), just before the World War I, the estates of Paris decedents made up over 26 percent of the French total.

[3] Rents were regulated in Paris discontinuously between 2015 and 2017 and have been regulated again since 2019

[4] HLM are intended to provide housing for disadvantaged or low-income people. They are are owned by specific entities, private or public.

[5] The full list is defined by Art R151-28

ferent spatial effect making them more or less efficient to impulse more social diversity. For instance, the 2009 regulation, which was the most restrictive since it imposed compensation within each district, succeed to foster the redevelopment of public dwellings in the center of Paris. In contrast, the 2011 law, and to a lesser extent the 2014 law, were less restrictive in high-demand area because the compensation could be done in other districts. For instance, an investor that want to transform x square meters of private housing in offices (or in short-term rentals) at the foot of the Eiffel Tower, could compensate by converting x square meters of offices into public dwelling at the periphery of the compensation area. We show that this relaxation of the spatial constraint increased the redevelopment of social housing at the periphery but not in the center, where the concentration of the richest population is the most deeply rooted. In support of this result, our research indicates that these laws have exerted no significant influence on social diversity as measured by occupation.

Our paper contributes to a large literature on the effects of local regulations on the supply of housing in general (Turner et al., 2014, Gyourko and Molloy, 2015, and Glaeser and Gyourko, 2018) and in public dwelling in particular. In the U.S., public housing development is no longer a major policy objective (replaced by housing vouchers), and in several cities, plans for demolition have been implemented. Several studies have then analyzed the effects of these demolitions on income and racial segregation (Almagro et al., 2023, Chyn, 2018, Jacob, 2004).

In France, much of the research has focused on the consequences of the Solidarity and Urban Renewal act[6] that aimed to foster the building of public housing in cities where this supply was scarce (Gobillon and Vignolles, 2016, Beaubrun-Diant and Maury, 2022, Jaupart, 2020). By analysing the within-municipality segregation effect of this law, over the 1998-2008 period, Chapelle et al. (2022) find a significant positive effect on the construction of public dwellings, but little impact on low-income segregation. Our analysis is complementary to these approaches, instead of analysing demolition (like in the U.S. case) or construction (in France), we analyse redevelopment of public housing from commercial unit. In a city like Paris, where the possibility to build public housing from scratch is limited, redevelopment represents an inter-

[6]Since the Solidarity and Urban Renewal (SRU) law ("loi de solidarité et renouvellement urbain") of 2000, a minimum quota of social housing per municipality has been established: social housing should represent at least 20% of the total stock of housing. Municipalities under the quota are required to build affordable housing, or be subjected to penalties. In 2018, the Elan's act ("Evolution du Logement, de l'Aménagement et du Numérique") has both increased this minimum rate and the penalities.

esting alternative to reduce income segregation. Regarding urban redevelopment, many studies have analyzed the conversion of office, such as Beauregard (2005) that analyzes how office conversion subsidies have changed the lower Manhattan after the New York City's revitalisation plan. Cheshire and Kaimakamis (2021) analyse a new british regulation implemented in 2013 that provides an automatic right to convert offices to residential use. Exploiting the fact that central location in London were excluded, they estimate the impact on prices, and find a statistically significant increase in value of buildings that became entitled to convertion (they find a 50% premium for these offices). Several articles have also analyzed how city hall have implemented laws that restrict the conversion into housing for short-term rentals (often called Airbnb's laws). For instance, Robertson et al. (2022) find that these policies reduce the amount of short-term rentals in Bordeaux by a significant number of 316 rented days per month per district on average. We share with this literature a similar empirical strategy based on regression by discontinuity, but we propose to go beyond the border-discontinuity by also analyzing the spatial effect of these policies in the city center (using a synthetic difference-in-differences). Furthermore, by analysing conversion of commercial use and social housing redevelopment our study is more general.

Section 2 presents the different laws and the historical urban background in Paris. Our empirical analysis is divided in two parts, in Section 3 we analyse the effect of the laws at the border of the compensation area and in Section 4 in its center. In Section 5 we analyse the impact of these laws on seggregation by occupation. The last Section concludes.

2 Background

2.1 Conversion into housing

The Paris metropolitan area is widely recognized as the archetypal city where the central area hosts households with a higher average income compared to the surrounding suburbs (Brueckner et al., 1999), a pattern that has been observed since at least the time of the industrial revolution. Starting in the middle of the nineteen century, the renovation of the city, known as the Haussmannization, had for consequence to gentrify the city and to partly drive out the working classes (Chevalier, 1958; Smith, 1982). The de-sindustrialization and then the methamorphosis of Paris

to a global consumer city,[7] linked to its persisting centralization of the french political, financial and mediatic organizations have magnified this residencial seggregation between the city center (*alias intra-muros*) and its periphery. The gentrification from the West of Paris (an historical central place for the upper class), has spread to the entire historic center of the city. By contrast, from the 1960s onwards, the suburbs disproportionately attracted the low- and middle-income classes (Clerval, 2010).

While some countries, like the United States, have a long tradition of decentralization regarding land use and housing regulation (Glaeser and Gyourko, 2018), until recently, France was highly centralized, with national planning agencies and direct directives from the central government. The 2009's local regulation studied here is the consequence of a significant change toward decentralization that occurs just several months before with the law called 'modernization of the economy'. Pursuant to this law, the City of Paris has requested the transfer of jurisdiction from the State concerning the change of use of residential units.

2.2 The 2009 law

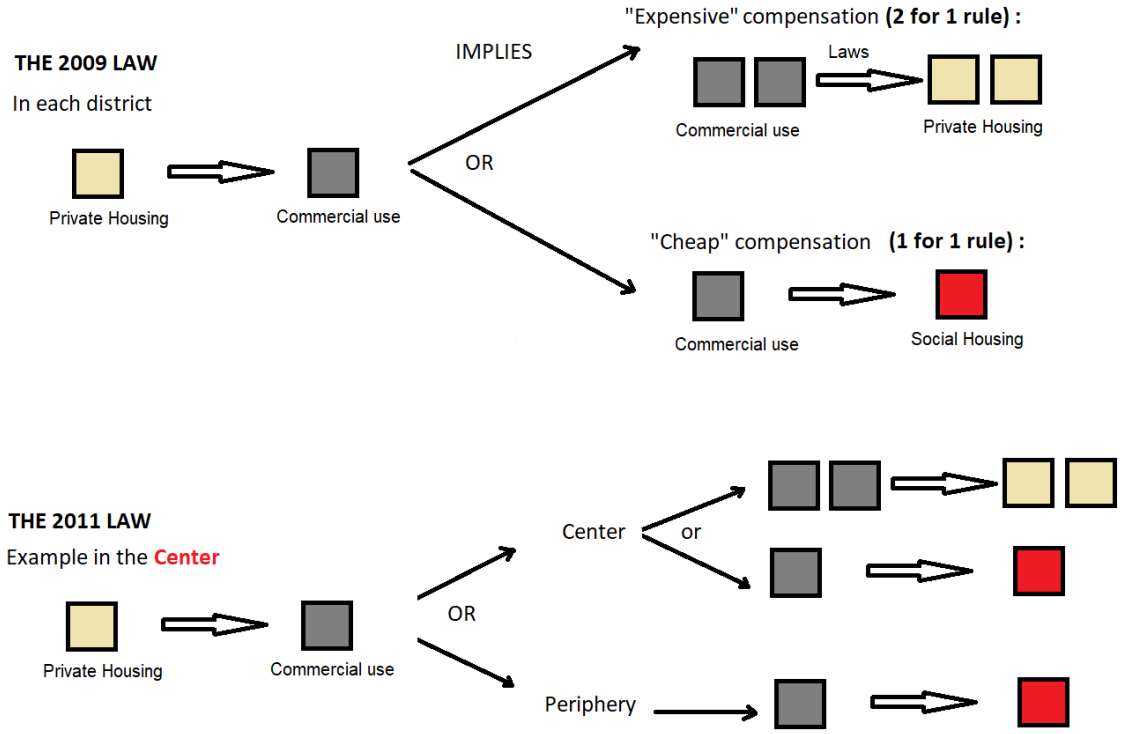
In 2009, a compensation zone is created, in which the surface of the private housing converted into commercial use should be doubled in the same administrative unit (called *arrondissement*) where the change of use occurs. To give an example, a Property Redevelopment Developer (PRD) that changes a building of 300m² of private housing into offices in the city center (e.g. Bourse district) should compensate by buying 600m² of offices (or other comercial premises) there and convert them into residential accommodation. In that case, the law fosters the redevelopment of private housing and reduces the surface of offices.

However, to increase the stock of social housing, the rule of doubling the surface does not apply for HLM. Thus in the previous example, if these 300m² private housing are changed into commercial unit, but with a choice to compensate by the redevelopment of public dwelling, then only 300m² of commercial unit should be converted (and not 600m²). This provides a clear economic advantage for the re-

[7] Defined as a city in which consumption both attracts mass tourism, entrepreneurs and high skilled workers (Glaeser et al., 2001). This spatial sorting can be explained by the fact that high amenity centers facilitate social interactions (Glaeser and Gottlieb, 2006) and provide a wide variety of goods (Lee, 2010) that are valuated by high income individuals. Furthermore, the gentrification of central city location can also be explained by the fact that 'low-leisure-high-skill' households have pronounced proclivity towards these locations that enable to save the time of commuting (Edlund et al., 2021).

development of public housing in absolute term but also in comparison to private housing. Figure (1) below summarizes these different changes of use,[8] that may be decomposed into two stages with a first step concerning the choice of commercial redevelopment and the second one regarding the compensation chosen.

Figure 1: Redevelopment under conversion laws



This policy covers various different situations and investors. For instance, beside the previous example, a landlord that converts its housing into a short-term rental is also concerned by the law.

An interesting aspect is that this policy, with its spatial constraint requiring conversion within the same administrative unit, can have vastly different effects depending on the initial demand of redevelopment (first stage). In districts where the growth of redevelopment from housing to commercial unit is strong, such a law introduces an incentive to compensate by redeveloping public dwelling which is

[8]There is a distinction in the French administrative vocabulary between a "change of use" and a "change of designation/purpose" (called *destination* in French) that concerns for instance a *permanent* change from a commercial premice to a private/public housing or vice-versa. We come back on this definition/explanation with more details in the data section.

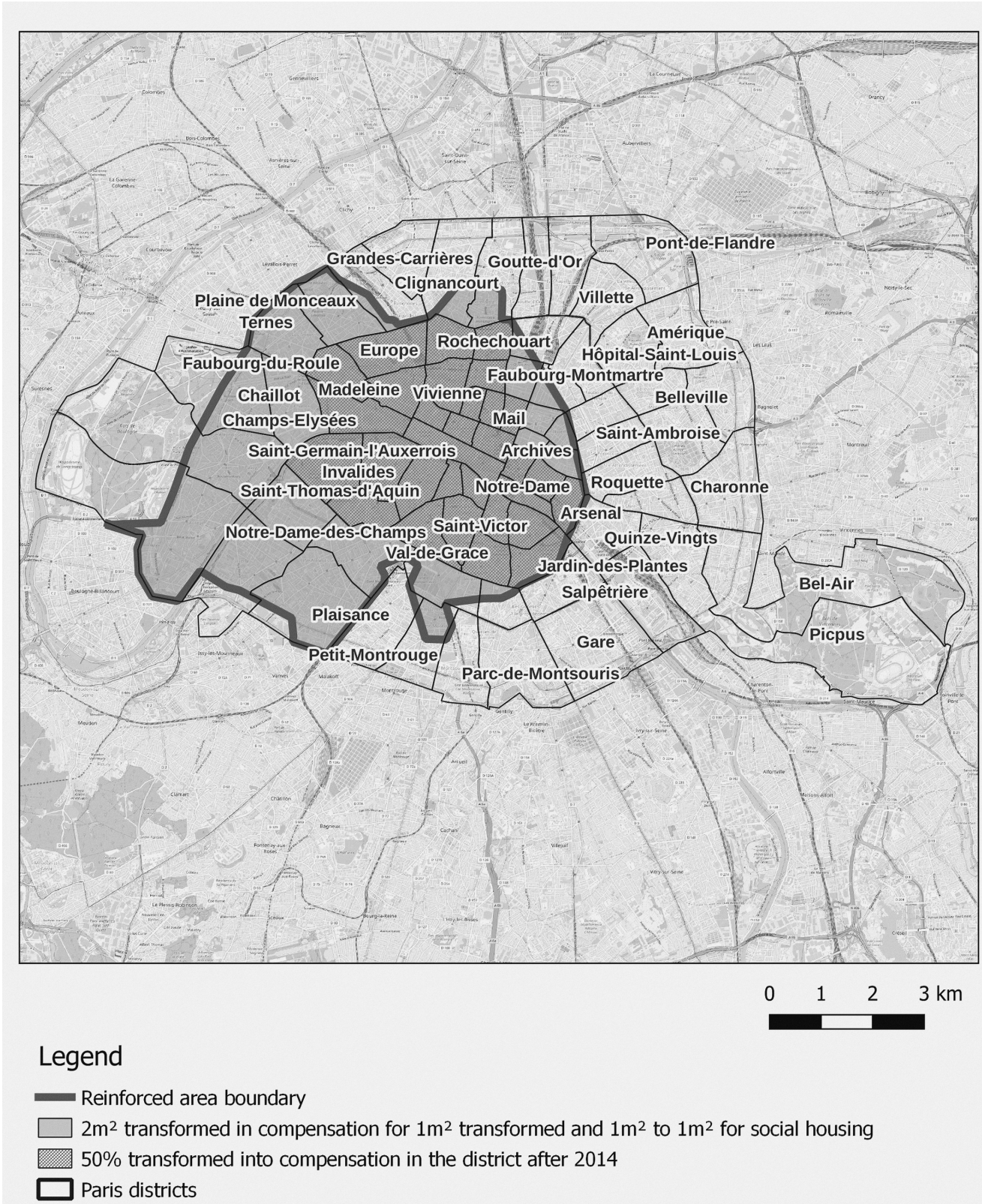
always the less costly choice (the redevelopment of private housing requires twice more space).[9] In contrast, in districts where the initial change of use is low, then this regulation may not have significant effect. In other terms, the law introduces a spatial complementarity (in two steps) between the redevelopment of commercial unit (first step) and the one of public dwelling (second step) at the district level. By defining the "periphery" as neighborhoods located on the internal border of the compensation zone, we can summurize this discussion as follows.

Proposition 1. *Testable Implications (law of 2009). A conversion law that stipulates compensation in the same district (under the asumptions of a high demand of redevelopment in the center, and a weak demand of redevelopment at the periphery), implies a significant increase in the number of social housing in the center. No significant effect on social housing at the periphery.*

Map (2) represents by a black line the compensation zone of this law, also called "reinforced" or "enhanced" area. In Section 3 we are going to define more precisely what we consider as the peripheral neighborhoods at the internal border of this compensation zone, and in Section 4, the districts of the center. For now it simply matters to notice that districts/neighborhoods, which are delimited by a gray line in Map (2), are defined by the "IRIS" classification which is the standard unit for infra-municipal data in France (population generally falls between 1,800 and 5,000). It is also important to notice that the periphery of the compensation zone does not refer to the outer rings of the Paris metropolitan area. Rather, it is still within the city of Paris and recognized as an area with a shortfall in social and private housing relative to demand.

[9] In an online Appendix (10) we propose a simple model to better understand the mechanism at play under different assumptions.

Figure 2: Compensation Zone



2.3 The 2011 and 2014 laws

In 2011, the law is amended to be less restrictive in the center. All the enhanced compensation zone is concerned by the possibility to compensate for public dwelling (i.e. not only in the arrondissement in which the change of use/designation occurs) but not for private housing (in that case doubling the area of private housing to compensate should be done in the same arrondissement). To give an example an owner in the city center that wants to change the use of his dwelling from residential to commercial, for instance to develop short-term rental (e.g. Airbnb), can compensate by converting commercial unit in public housing at the periphery. This simple change in the spatial opportunities to compensate can modify the different incentives. It becomes easier now to develop commercial units in the center without compensation there which opens the door to a reduction of public housing in the center. Indeed, since redevelopment of public dwelling is less costly than private housing (requiring half of the space of commercial unit to change) and less costly at the periphery than in the center, such a law favors public housing at the periphery. Then this new regulation totally reverts the spatial incentive to redevelop HLM. While the 2009 law fosters their redevelopment where the demand of change of use was high (in the center), the 2011 law may stimulate them in places relatively less attractives (namely where the price of revelopment is relatively low).

Proposition 2. *Testable Implications. A conversion law that enables to compensate commercial redevelopment in the center by public dwelling at the periphery implies (under the assumption of a high demand of commercial redevelopment in Core, and a weak one at the Periphery), a significant increase in the redevelopment of social housing at the periphery and no significant effect at the center.*

A new regulation is adopted in 2014 that partially come back to the seminal law of 2009. Eight districts in the center of the city are targeted with a compensation rule establishing that at least 50% of the surface should be compensated there (the eight districts are represented in dark gray in Map 1). The results of the 2014 are thus less clear and perhaps deserve, even more than the other laws, an empirical investigation.

2.4 Details on the compensation right

The compensation can be carried out directly by the applicant, who offers as compensation premises that he owns or buys (as in our previous examples), or indirectly, by purchasing a compensation title/right (called "droit de commercialité") from a third party that transforms premises into housing. To obtain titles of compensation, the applicant can turn to specialized companies or to social landlords, who carry out operations of transformation of offices/shops (and so on) into housing and can thus propose premises in compensation.

This transfer of commerciality from a property for use other than housing to a residential property, allowing the applicant to obtain a change that is permanent. For him the compensation title looks like an administrative cost to convert its building.

It is important to notice that there is no official price for these titles, the prices are negotiated between the buyer and the seller. They vary depending on the location of the property. According to the Housing and Habitat Department of the Paris city,[10] the average price over the period is around 1,600 € per square meter, with very significant variations, from about 400 € per square meter up to 3,000 € per square meter in the western and central districts of the capital where demand is highest. Artigalas and Richaud (2018) and Morel (2017) confirm that the cost of compensation title is smaller than the housing prices but still significant.

2.5 Details on exception and implementation

Since the origin, the law has taken into account exceptions (i.e. no conversion) for liberal professions, first floors, organizations exercising a mission of general interest. The team in charge of the implementation of this regulation is relatively small (twenty people in 2014 according to Plottin, 2016) but composed of inspectors with wide-ranging prerogatives who carry out on-site investigations. Infractions are severely repressed, the amount of the fine has been set at €25000 in 2009 and has been doubled in 2016.[11] The president of the court orders the return to the previous use for the housing converted without authorization within a given period of time. At the end of this period, the court can impose a fine of up to €1,000 per day and per square meter of the unlawfully converted housing. A fine of €80000 and one year imprisonment are also included in the law for false declarations.

[10] https://cdn.paris.fr/paris/2021/06/11/e22f26b33f762b28aae60e1866c10041.pdf

[11] Article L651-2 of the "Code de la construction et de l'habitation"

2.6 Data and descriptive statistics

2.6.1 Dependent variable

Change of what?

In French administrative lexicon, there is a distinction between *change of use* and *change of designation* (or *purpose*, called "destination" in French). A change of use refers to the conversion of a residential unit into a commercial property, but this change is linked to the current owner of the unit and should be temporary, enduring only while the commercial operation occupies the unit. No physical modification of the unit is allowed; the change is strictly in the property's utilization. Conversely, a change of designation, for instance from a commercial property into a residential unit, is associated with the property itself, not the owner. This change is permanent.

If the consequence of the law is always a change in designation, it's implementation can be, in some cases, due to a change of use.

For instance an owner that want to rent one room on Airbnb (more than 120 nights in 2014), can make a simple *change of use* of its room from a private to a commercial space, but should compensate by generating a *change of designation* from a commercial unit to a private or public unit. Here we have data on change of designation toward public dwelling, and not on change of use.

These data come from the Land Registry Files provided by CEREMA (Center for Studies and Expertise on Risks, Environment, Mobility, and Spatial Planning).[12] This dataset enables the identification of housing units that have undergone a change of designation, with the date of the last change made (including social housing units). The data used covers the housing stock as of January 1st, 2020, in the departments of Paris, Hauts-de-France, Seine-Saint-Denis, and Val-de-Marne and provides the changes of designation over the period 2006-2019. These files provide the description and geolocation of all buildings and land parcels.

This dataset is exhaustive and provides all the redevelopment of social housing being own by social landlords or by private landlords (in that case identified by a tax exemption that is specific by its duration, namely granted for the first 25 years after its creation). More precisely this includes social housing, labelled PLAI that concerns very poor households, PLUS for low-income and finally PLI and PLS that

[12]The CEREMA is a public institution responsible for processing files from the DGFiP (Directorate General for Public Finance), which centralizes fiscal information and characteristics of properties in France.

are considered to be for the middle income in tense areas.

Residential units are identified based on the nature of the premises, that is, units registered as houses or apartments and categorized as residential housing.

The data are aggregated at the IRIS neighborhood level (often called districts or neighborhoods in what follows) and corresponds to the number of square meters that have undergone a change of designation.

About zeroes (no change in use)

Neighborhoods where there are no housing units that have undergone changes in designation are taken into account in the estimates (the value is equal to 0). The choice to keep these neighborhoods in the analyses is justified by the fact that many neighborhoods, particularly in the compensation area before the regulation was put in place, have few square meters converted. For example, in 2006, 87.53% of the neighborhoods in the compensation zone had not undergone changes in use towards social housing, a share that rises to 97.59% in the high-income districts of the 1st, 7th, and 8th arrondissements of Paris. This proportion decreases by 12 percentage points in 2019.

More generally, in 2006, 65.04% of the neighborhoods in the compensation zone had not undergone changes in use towards housing units intended for private occupation. This share drops to 18.34% in 2010 after the first change in use rule, and then to 4.4% in 2019, the last year of observation. These figures can show the importance of considering neighborhoods with no transformation. As the goal of this study is to identify the impact of the implementation of compensation rules in Paris, keeping these zeroes enable to observe the evolution of transformations in neighborhoods previously not subject to change of designation (and which are, in fact, implicitly targetted by the different laws).

2.6.2 Explanatory variables

Income

Income levels, by impacting the demand for private housings, directly affect their prices and may subsequently diminish the supply of redevelopment from private housing into commercial units. On the other hand, observing the goods market, a concentration of high incomes can encourage commercial activities, which in turn

boosts the demand for such redevelopment. The introduction of this variable however poses several challenges, first reverse causality is likely, the level of income in one district may directly depends on the share of social housing leading to a bias in our estimates. Furthermore, income are potentially correlated with other variables of controls. Finally, controlling for incomes but not for other variables that simultaneously affects it and our dependent variable (which is quite unavoidable) creates a new pattern of bias, since the variable of income is in that case a collider or, in the word of Angrist and Pischke (2009), a bad control. Such a bad control can provide false results by, for instance, changing the sign of coefficient of interest. Then, we introduce income progressively to detect multicolinearity. We also consider a rich set of fixed effects to control for omitted variables in order to reduce the collider bias when income is considered, and finally we use other variables of controls than income for which the poblem of reverse causality is less acute.

Income data comes from INSEE (Institut Nationale de la Statistique et des Etudes Economiques) and represents the median annual income of individuals living in each neighborhood studied between 2006 and 2019. To give an idea of income distribution, the average median income in the compensation zone was €27636 per year in 2006, compared with €35877 in 2019. In the control zone, median annual income was €18961 in 2006 and €23883 in 2019.

Short-term rentals

As explained in the data section, any change of use from a private unit to a commercial unit to develop short-term rental *cause* a change in designation. In other term, Airbnb is a mechanical determinant of change in designation from commercial unit to residential unit. Obviously we cannot rule out reverse causality, namely that an owner entering in a new designated private housing chose to change the use of one part of it its dwelling, however such a change is more likely to happen some years latter. A second problem of this control, is that it is not sure that all the owners that enter in the short-rental market declare it to the administration, in particular at the start of the period.

Airbnb data comes from the Open Data Soft platform, a French company that makes these data available. The origin of these data comes from Inside Airbnb, a site created by Murray Cox, an American activist, making available data from short-term rentals web-scraped on the Airbnb site in the city of Paris. As we don't have

the historical data, we used the web-scraped information on the October 3^{rd} 2020 using the account creation dates of owners with a listing on the Airbnb site. These data indicates that the last Airbnb account creation was in 2017, furthermore there is few data before 2012, then when using these controls we restricted our analyses to the period 2012-2017.

Reputation of secondary schools

To consider another aspect of the location choice of households that plays of the choice of redevelopment, we use a measure of the reputation and quality of schools. There is indeed a large literature that emphasizes the role of schools in residential choices (Bayer et al., 2007). In France, parents are partially constrained by a legal map of school districts that depends on the residence, which explains why the residential choice and the school choice are linked. Like the income variable, a simple indicator of the reputation/quality of schools is problematic due to reverse causality. It can be negatively affected by the number of social housing in this district. We thus chose indicators that may be less prone to this problem. These indicators, named "indicators of added value" (IAV) of secondary schools, measure the school's ability to support its students through to the baccalaureate (namely the first academic degree that grants the completion of secondary education).

Computed by the statistics department of the French Ministry of Education, hereafter DEPP (Direction de l'Evaluation, de la Prospective et de la Performance), the added value is obtained by the difference between the result of each student and its expected result. The modeling relies on a multilevel logistic estimation at the student level. The expected result, for a student, is obtained by applying the model's coefficients to their individual characteristics (e.g. grades) and collective characteristics (socio-economic variables such as parents' professions), from which the effect of the school is subtracted. The predicted rate corresponds to the probability of the student's success (or access) if they were in an "average" high school. Or to put it differently, since these indicators control for the profile of each school according to the social background and age of the school's pupils, questions about the endogeneity of this variable are less obvious than for simple indicators of performance.

Another interest is that these indicators are regularly used to rank secondary schools by newspapers[13] and then represent an available source for individuals.

[13]These indicators have an history that is really linked to their mediatization (Evain, 2020). They

3 Effects of conversion laws at the dividing line

3.1 Empirical strategy

3.1.1 Spatial Regression Discontinuity Design in Differences

The simple fact that these laws may have particular effects at the periphery of the compensation zone logically drives the empirical strategy toward a Spatial Regression Discontinuity design (SRD, Keele and Titiunik, 2015). Indeed the housing market and even the carasteristics of neighborhoods are similar on both side of the border (see the black line in Map 3), enabling to defend that the sole difference between districts treated and untreated around the dividing line comes from the law of compensation. Such an assumption is however strong, we cannot rule out that people chose to sort on either side of the borders according to characteristics that we do not control for. This could biased our analysis by creating significant differences between treated and untreated units, or to put it differently, the control group may no longer represents the potential outcome of the treated group if not treated. It is also possible that for each year the compensation law was enforced, other policies have been implemented within the compensation area and not outside this zone. We are not aware of such a possibility, but we may have overlooked it. In that case, the treatment becomes a combination of multiple treatments or interventions that are applied at the threshold. This potential problem of compound treatments makes less credible the isolation of the causal effect of the compensation law with the SRD strategy.

We thus use a difference in discontinuity (Grembi et al., 2016), hereafter diff-in-disc, that enables to control for multiple treatments and time-invariant factors by time differenciation. More precisely the diff-in-disc makes the difference between the pre-treatment regression discontinuity (that identifies time-invariant effects of other laws as well as the discontinuity due to time-invariant sorting) and the post-treatment regression discontinuity (which measures again the two previous discontinuities but also in addition the treatment of interest). This difference enables to recover the treatment effect of the compensation laws (Butts, 2021).[14]

were created in 1987 by the French Ministry of Education as an administrative, and not public tool, to manage secondary schools. But after an inadvertent leak in the media, they became public in 1993 and have since been regularly used to rank secondary schools by newspapers.

[14] See also Eggers et al. (2017) for discussions.

We then estimate the following equation:

$$Y_{it}^{\flat} = exp(\lambda_i^{\flat} + \sum_j \varphi_j^{\flat} Z_i^{\flat} T_j + \sum_j \gamma_j^{\flat} Z_i^{\flat} D_i^{\flat} + \sum_j \delta_j^{\flat} D_i^{\flat} T_j + \sum_j \beta_j^{\flat} T_j D_i^{\flat} Z_i^{\flat} + \theta_t^{\flat} + \Gamma_{it}^{\flat}) \varepsilon_{it}^{\flat}, \quad (1)$$

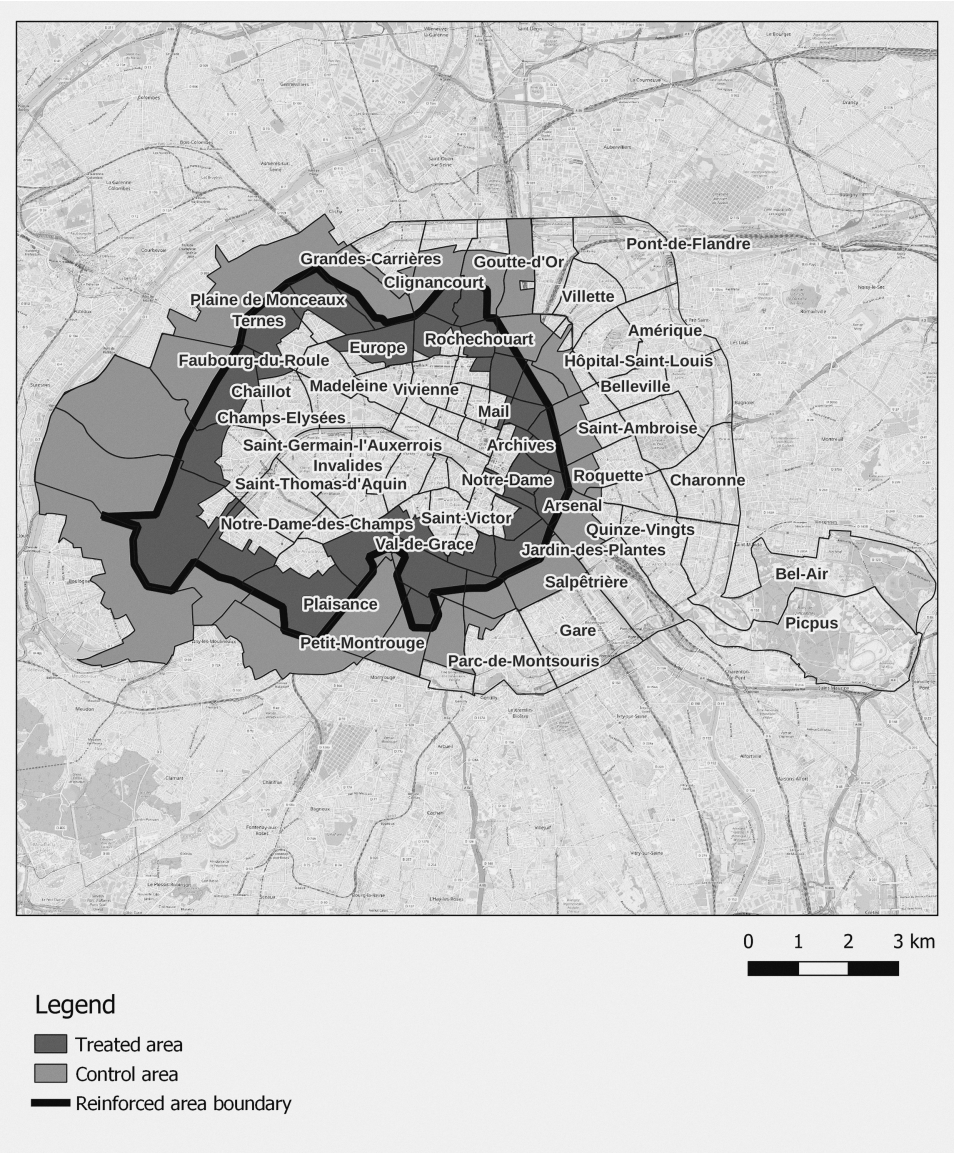
where $Y_{it}^{\flat}$ is the number of square meters of social housing newly created (i.e. resulting from a change of designation) in the neighborhood i at the time t. As explained in the data section, this variable includes neighborhoods with no transformation and then lead us to use the Pseudo Poisson Maximum Likelihood estimator.[15]

This dependent variable is delimited geographically according to a particular distance to the border treatment zone. For instance with a bandwidth $\flat = [-300, 300]$, 300 meters are taken on both side of the limit of the treatment area. We estimate this equation seven time by increasing this spatial window to 100 meters, such as $\flat = \{[-300, 300]; ..., [-900, 900]\}$.

Figure 3 presents a example with a bandwidth at [-600,600] for the year 2014. Treated districts are represented in dark gray, the control group is in bright gray.

[15]Similar results are obtained with OLS (without zeroes) in the Online Appendix (14).

Figure 3: Treated and Control Areas in the Difference in Discontinuity (bandwidth: 600 meters)



T_j is a dummy taking one after each policy j implemented and zero otherwise, with $j = \{2009, 2011, 2014\}$. $Z_i^\flat$ a binary variable taking one for treated housing inside the compensation zone and zero for housing in the control group outside this zone. These two zones are obviously defined spatially by the bandwidth $\flat$. $D_i^\flat$ is the distance between the district (IRIS) and the border treatment zone. $\lambda_i^\flat$ and $\theta_t^\flat$ are repectively individual fixed and time effects. $\Gamma_{it}^\flat$ is the vector of controls discussed in the theoretical model and described in the data section.

Standard errors are clustered at the district level to account for arbitrary serial

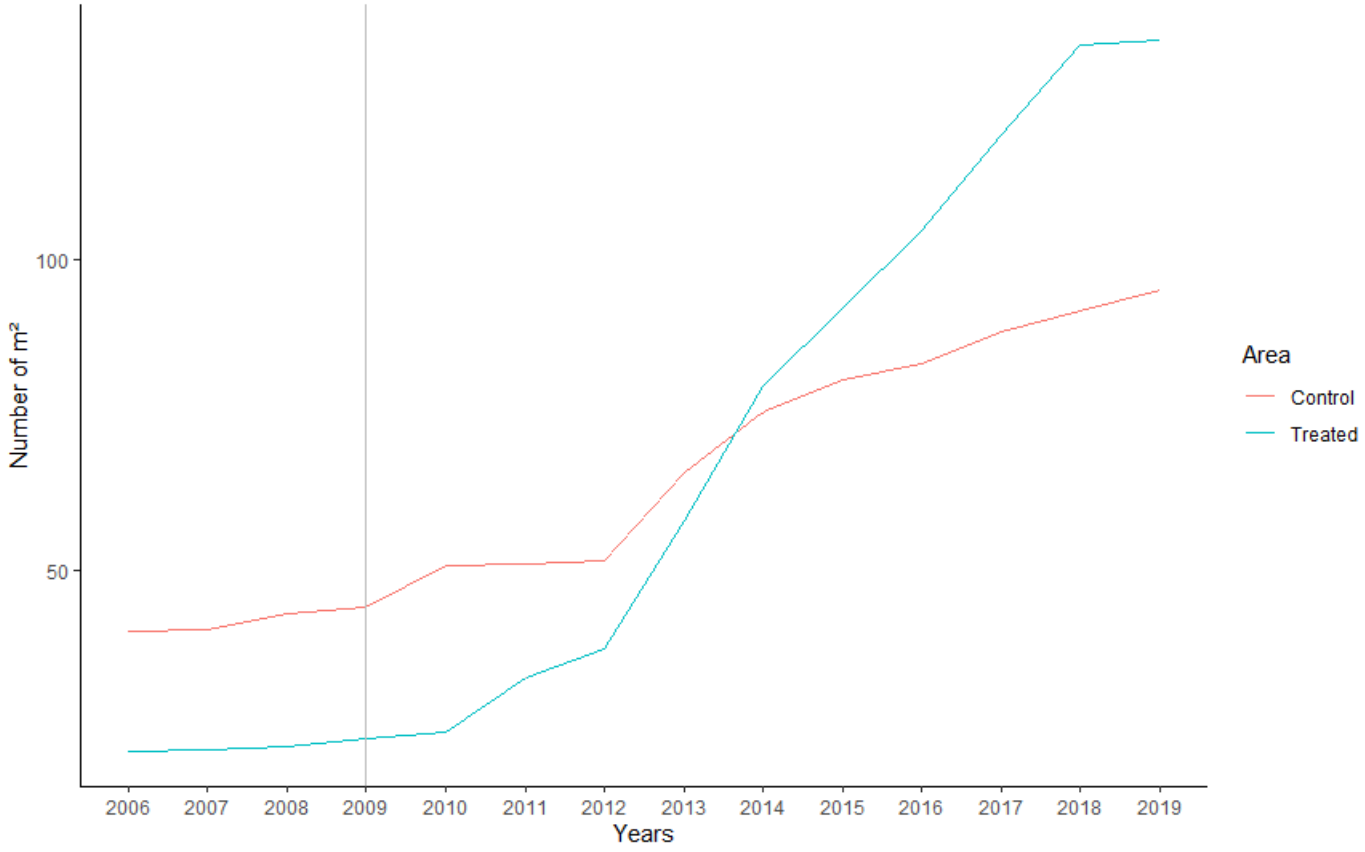
correlation in the error term (Bertrand et al., 2004, Abadie et al., 2022). The coefficients of interest are $\beta^{\flat}_{2009}$, $\beta^{\flat}_{2011}$ and $\beta^{\flat}_{2014}$.

The fact to introduce in the same regression these three treatments have pros and cons.

The main problem, not resolved in the literature with multiple treatments, is that the parallel trend assumption is likely to hold only for the first treatment, namely the 2009's policy. The raw data presented in Figure (4) show the number of square meters converted. It clearly shows that the treated and control groups followed a similar trend before the implementation of the first law. Subsequently, there is a noticeable increase in the conversion of areas within the treated group as compared to the control group, particularly after the year 2010. This suggests the positive impact of the various laws, although it complicates the identification of the effects, in particular for the last policy introduced. Indeed, from this figure, the assumption of parallel trends before the enactment of the 2014 law seems quite heroic, to say the least.

However it is important to note that this figure represents unadjusted data, one might expect that the parallel trends to the pre-2011 and pre-2014 laws would be partially corrected when controlling for other factors, as opposed to the trends depicted in this basic plot. In particular the fact to introduce simultaneously the dummies of these three laws in the same equation, partially control for the effect of each of them. For instance the same estimation with only the dummy of the 2014 law, could lead to a biased estimation of $\beta^{\flat}_{2014}$ that takes into account the effects of the 2009 and 2011 laws. To assess the magnitude of this bias, we estimate again Equation (1) by analyzing separately the three different laws in the Online Appendix (16), we find similar results.

Figure 4: Treated and Control Areas in the Difference-in discontinuities (bandwidth: 600 meters)



By examining the three estimates across various spatial windows, we perform another type of robustness check. The estimation with the narrowest bandwidth is likely to best satisfy the conditions of the Diff-in-Disc approach, as treated and untreated individuals are geographically close enough that we can reasonably expect them to be similar. Nevertheless, by employing a triangular kernel that assigns weights based on each observation's distance to the border, we give more importance to observations near the spatial cutoff. As a result, even with a larger bandwidth, the potential outcome of the treated group can still be approximated by the untreated district, given that observations closer to the border are prioritized. Then, we also provide results in the Online Appendix (12) with the Epanechnikov and Uniform distribution of weights.

Finally instead of using this long list of ad-hoc bandwidths, we use the Mean Squared Error (MSE) optimal bandwidth choice for the local-linear regression point estimator proposed by Imbens and Kalyanaraman (2011) as well as the CE-optimal

neighborhood of Calonico et al. (2014) that provides a smaller neighborhood and enables to have the smallest coverage error (CE) probability.

Identification issues of the Difference in Discontinuity. As in standard RDD, manipulation of the assignment variable threatens the validity of identification (McCrary, 2008; Imbens and Lemieux, 2008; Lee and Lemieux, 2010). Such a manipulation is unlikely here, agents in the treated group that request a conversion cannot pretend to be in the control group where there is no regulation without taking significant risks. As explained in the previous section, the conversion is based on the address of the housing, inspectors control requests and a fine of €80000 is set for false declaration. Moreover once the manipulation is detected, the using should return to the previous use (with additional fines).

An issue that can jeopardize the identification is the endogeneity of the zone, in particular the spatial discontinuity (the border line), may not be exogenous. Such a possibility is not obvious since the compensation zone has been drawn on a past regulation that concerns parking lots and thus for a very different motive than the one study here.

Finally, like in standard difference-in-difference analysis, the identication rests on the assumption of parallel trends, here local parallel trends.

We also propose an alternative approach to the diff-in-disc by using a Synthetic difference-in-differences method in Appendix (9). All the results presented in the next Section are verified with this approach.

3.2 Results at the Periphery

Table (1) presents the results of the spatial difference-in-discontinuity with different bandwidth choices (see Appendix 12 for five additional ones) and various weight distributions to study the robustness of our result at the periphery of the compensation zone.

We find that no matter the assumptions made on the bandwidth, the 2009 law's initial implementation is not statistically significant.

This finding is in line with the expected results discussed in Proposition 1. During that period, the demand for redeveloping private housing into commercial units (first stage in Figure 1) was likely low at the periphery of the compensation zone. For instance, this period is in the aftermath of the financial crisis, which may have

hit the periphery harder than the center, limiting the demand of commercial redevelopment. Consequently, the law did not have any significant impact on public dwellings in this area (second stage in Figure 1). This situation highlight the complementarity effect that this regulation establishes between commercial and public redevelopment. During periods of economic downturn, this regulation fails to promote the redevelopment of public housing, yet it is precisely during such periods that the availability of commercial spaces (or offices) due to bankruptcies could facilitate the redevelopment of public housing at minimal costs.

On the contrary, Table (1) presents the significant role that the 2011 and 2014 reforms have played in shaping the changes in social housing. The coefficient of 0.643 and the corresponding elasticity around 90% suggest that the 2011 reform, in particular, has had a substantial impact. This confirms the mechanism behind the results presented in Proposition 2. The displacement of compensation from the center to the periphery has changed the geography of HLM redevelopment. These laws appear to have led investors to focus on redeveloping commercial units in the city center, opting to compensate by redeveloping public dwellings at the periphery, which typically represents the most optimal choice for them. Furthermore, this period is marked by the growth of Airbnb, initially concentrated in the center. This growth may have stimulated the redevelopment of public dwellings at the periphery, in response to these legislative changes.

The 2014 reform seems to have a lesser effect, with a coefficient ranging between 0.4 and 0.5. This aligns with its definition, as it is more restrictive in the Center than the 2011 law (50% of the compensation should be done in the Center, which reduce the displacement effect of compensation at the Periphery) but less so than the 2009 one. [16]

[16] See Online Appendix (17) for a placebo test.

Table 1: Social Housing Change from Difference in Discontinuities

Distrib of weights	Uniform		Epanechnikov		Triangular		Triangular	
Bandwidth choice	ad-hoc						CE-opt	MSE-opt
Bandwidth (in meter)	[-300,300]	[-600,600]	[-300,300]	[-600,600]	[-300,300]	[-600,600]	[-461,461]	[-1314,1314]
Treated in 2009	0.179	0.0416	0.247	0.116	0.240	0.144	0.208	0.0114
	(0.192)	(0.155)	(0.185)	(0.143)	(0.184)	(0.146)	(0.165)	(0.167)
Treated in 2011	0.643*	0.766***	0.666*	0.669**	0.665*	0.658**	0.634*	0.620***
	(0.376)	(0.279)	(0.389)	(0.309)	(0.390)	(0.322)	(0.359)	(0.222)
Treated in 2014	0.562**	0.564***	0.488**	0.564***	0.460*	0.545**	0.507**	0.522***
	(0.245)	(0.208)	(0.246)	(0.218)	(0.244)	(0.221)	(0.234)	6.426***
Constant	6.659***	6.164***	6.769***	6.459***	6.879***	6.592***	6.726***	(0.137)
	(0.116)	(0.166)	(0.0877)	(0.134)	(0.0742)	(0.114)	(0.0997)	
Observations	1,568	2,352	1,568	2,352	1,568	2,352	2002	4,004
R^2 adj.	0.895	0.879	0.902	0.888	0.908	0.895	0.900	0.875

Notes: Standard errors are clustered at the neighborhood level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Results are obtained from a spatial difference-in-discontinuity using the PPML estimator. Individual fixed effects and time effects are introduced in all estimations. The dependent variable is the number/area of HLM converted (in m^2). Columns (1, 3, 5) and (2, 4, 6) present results for areas that are respectively delineated by 300 meters, and 600 meters on both sides of the boundary of the treatment area. The difference between these columns lies in the distributions of weights that follow a uniform, Epanechnikov, and triangular distribution respectively. Column (7) presents results with the Coverage Error (CE) probability neighborhood, and Column (8) utilizes the Mean Squared Error (MSE) optimal bandwidth. Each estimate includes neighborhood and year fixed effects

The results presented in Table (1) are robust to different definitions of the Periphery, but they do not consider any control variables. Our estimations include time effects to control for temporal shocks and individual fixed effects to account for districts with structural difficulties. However, they do not control for effects that vary over time and across individuals.

We then introduce the number of units converted that may influence the supply over time depending on the location as well as other variables that influence the demand side such as the median income in the district. As discussed at lengh in the data section, these variables generate several problems (multicolinearity, endogeneity) and are thus analyzed successively to observe how our coefficients of interest (β) are affected. Table (2) presents the results. The total number of conversion has a positive effect on the number of social housing (Column 1), while the median income has a negative effect (Column 2). In these two cases, the effect of the 2011 and 2014 laws are still verified as well as the unsignificant effect of the 2009 law. Finally the last column shows that fixed effects play a real role in controlling for the median income which are no longer significant. Finally the effect of the different laws are similar to those presented previously in Table (1).

Table 2: Social Housing Change from Difference in Discontinuities with controls

Bandwidth choice	CE-opt [-461,461]			
	Conversion	Income	All	FE
Treated in 2009	0.180	0.214	0.221	0.146
	(0.173)	(0.164)	(0.191)	(0.169)
Treated in 2011	0.560*	0.650*	0.542*	0.627*
	(0.337)	(0.348)	(0.325)	(0.340)
Treated in 2014	0.620***	0.511**	0.598***	0.462**
	(0.239)	(0.228)	(0.230)	(0.233)
Number of conversion	0.0408***		0.05***	0.01***
	(0.0043)		(0.006)	(0.003)
Median income (/100)		-0.003**	-0.004**	-0.003
		(0.0013)	(0.001)	(0.003)
Constant	4.35***	5.15***	5.19***	7.38***
	(0.648)	(0.930)	(0.893)	(0.709)
Neighborhood FE				✓
Year FE				✓
Observations	5726	5726	5726	2002
R^2 adj.	0.06	0.06	0.10	0.90

Notes: Standard errors are clustered at the neighborhood level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Results are obtained from a spatial difference-in-discontinuity using the PPML estimator. All estimations use a triangular distribution of weight with the Coverage Error (CE) probability neighborhood method. The dependent variable is the number/area of HLM conversions (in m²). Column (1) introduces the total number of conversions (in m²), Column (2) includes the median income in each district, Column (3) presents results with these two controls, and Column 4 incorporates individual fixed effects and time effects.

Obviously the previous controls does not encompass the richness of the determinants that drive the demand of conversion. We then introduce data on Airbnb (a good proxy of the change in use that directly cause the change of designation studied here). We also introduce indicator of schools added value that may influence the housing market.

As already mentionned, data on school added value and on Airbnb are not available for the whole period (only on 2012-2017) but enable to study the 2014 law in Table (3). As in the previous estimation, the total number of conversions is significant while the median income is not. Interrestingly, the coefficient of Airbnb is positive (when introduced alone) which is the expected effect of this law. However this positive effect loses its significance once fixed effects are introduced. Similarly all the indicators of school added values lose their significant impact once fixed effects are introduced. This illustrates both the challenge of identifying variables that influence

HLM conversion and the effectiveness of fixed effects in controlling for determinants that does not vary a lot over such a short period of time.

Table 3: Social Housing Change from Difference in Discontinuities with added value indicators for schools and Airbnb from 2012 in Paris intra muros

Bandwidth choice	CE-opt [-461,461]					
	Conversion	Income	School AV	Airbnb	All	FE
Treated in 2014	0.537**	0.446**	0.427**	0.452**	0.591***	0.404**
	(0.210)	(0.211)	(0.211)	(0.208)	(0.213)	(0.199)
Nb of conversion	0.033***				0.033***	0.013***
	(0.006)				(0.006)	(0.003)
Income (median)		-0.002			-0.003**	-0.002
		(0.001)			(0.001)	(0.002)
School Added Value						
Performance			-0.444**		-0.471**	-0.064
			(0.223)		(0.212)	(0.075)
Accompanying			-1.809***		-1.622***	-0.115
			(0.514)		(0.489)	(0.136)
Below expectation			-1.155**		-1.248**	-0.201*
			(0.506)		(0.492)	(0.110)
Selective			-1.243**		-1.169**	-0.017
			(0.483)		(0.456)	(0.106)
Airbnb				0.029***	0.034***	0.005
				(0.009)	(0.009)	(0.004)
Constant	4.62***	5.32***	5.33***	4.49***	5.54***	7.28***
	(0.572)	(0.812)	(0.640)	(0.607)	(0.877)	(0.601)
Neighborhood FE						✓
Year FE						✓
Observations	2118	2118	2118	2118	2118	768
R^2 adj.	0.037	0.035	0.074	0.033	0.134	0.936

Notes: Standard errors are clustered at the neighborhood level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Results are obtained from a spatial difference-in-discontinuity using the PPML estimator. All estimations use a triangular distribution of weight with the Coverage Error (CE) probability neighborhood method. The dependent variable is the number/area of HLM conversions (in m²). Column (1) introduces the total number of conversions (in m²), Column (2) includes the median income in each district, Column (3) presents results with indicators of the added value of secondary schools. Performance schools exhibit a positive difference in both access and success rates. Accompanying schools are those where students take longer to obtain their diploma, but where the dropout rate is low. Schools that fall below expectations have poorer results in both success and access rates in comparison to their predicted outcome. Selective schools are characterized by high schools with a high success rate difference and a low access rate difference. Column (4) introduces the Airbnb variables. Column (5) presents results with all these controls. Column (6) incorporates individual fixed effects and time effects.

4 The effects of conversion laws in the heart of Paris

To study how these laws have affected redevelopments in the center of Paris, we can no longer use the empirical strategy based on discontinuity. Indeed in that case the observations outside the compensation zone but near the border cannot be considered as valid countrefactuals of the treated in the center, districts are simply too different. One solution in that case is to build synthetic controls of the treated units, we then use the Synthetic Difference-in-Differences approach of Arkhangelsky et al. (2021), hereafter SDID, which reweights and matches pre-exposure trends.

The goal of this method is to weight the control units in the pretreatment period to make these different units comparable with the treated units such that the weighted control units are approximately equal to the pretreatment treated units such as :

$$\sum_{i=1}^{N_{control,pre}} w_i^{sdid} Y_{it} \approx \sum_{i=1}^{N_{traited,pre}} Y_{it},$$

with w_{it}^{sdid} the time weights t and units i multiplied by the dependent variable Y_{it} in the neighborhood i in year t. The time and unit weights are then used in a regression where the weights $\hat{\omega}_i^{sdid}$and $\hat{\Delta}_t^{sdid}$ minimize the difference between the treated and control units before treatment Z_{it} such as:

$$\hat{\tau} = arg\,min \left\{ \sum_i^N \sum_i^T (Y_{it} - \epsilon_{it} - \eta_i - \Gamma_t - Z_{it})^2 \hat{\omega}_i^{sdid} \hat{\Delta}_t^{sdid} \right\},$$

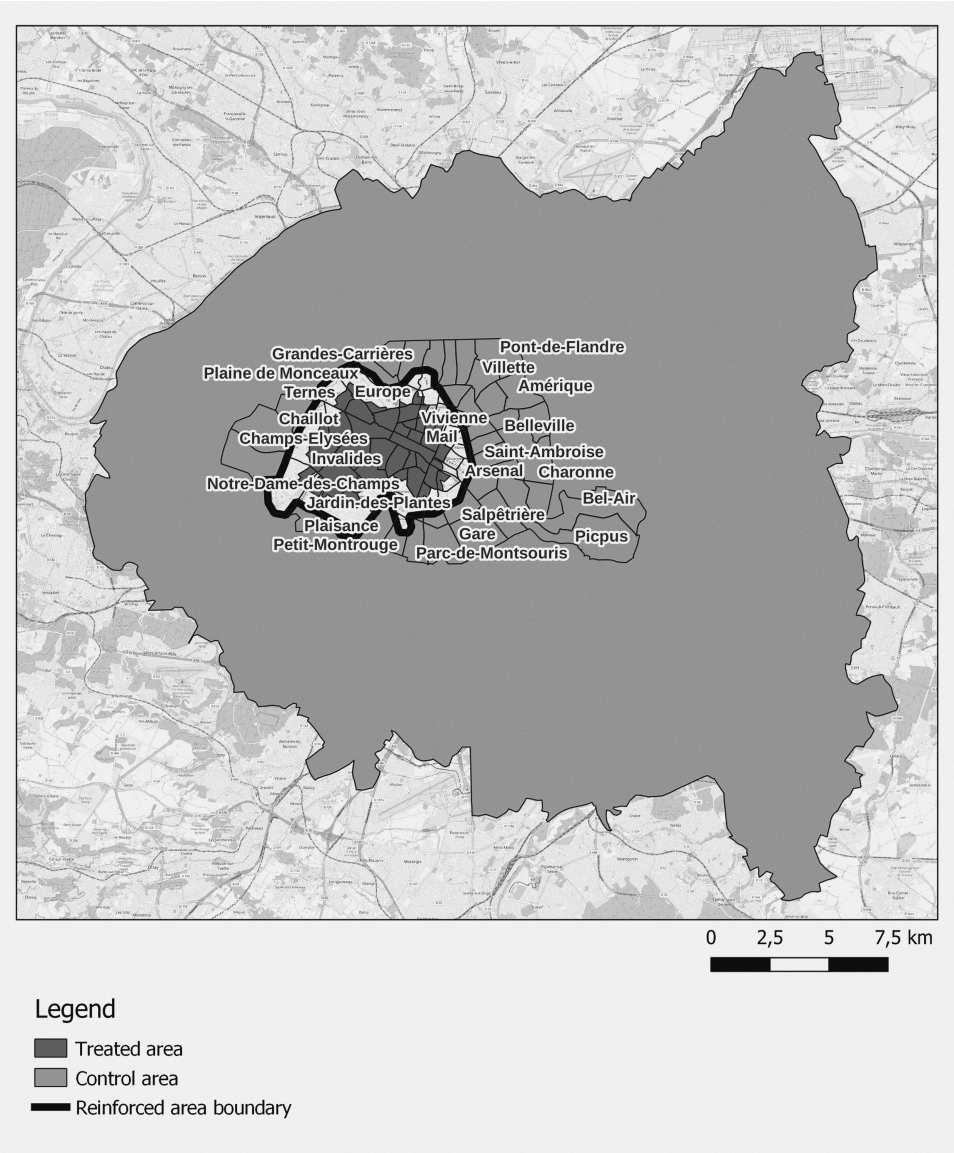
with η_i the neighborhoods, Γ_t the years, ϵ_{it} the error term and Y_{it} the dependent variable. The weights used to build the synthetic controls are presented in the Online Appendix (11).[17]

The SDID strategy is still estimated from Equation (1) with PPML and aim to estimate as previously the coefficients $\beta_{2009}^{\flat}$, $\beta_{2011}^{\flat}$ and $\beta_{2014}^{\flat}$.

Considering the buffer area that has its limit at 600 m of the treatment zone, we take as treated the districts that are inside the reinforced area but not in this buffer zone. Figure (5) presents this example for the year 2014, the treated districts are shown in dark gray, the synthetic control is built on districts located in the bright gray area.

[17] We also present results with the nonparametric synthetic control method developed by Cerulli (2020) in Online Appendix (15).

Figure 5: Treated and Control Areas in the Synthetic Difference-in-Differences (bandwidth: 600 meters)



Our testable hypothesis is that the law of 2009 had a more concentrated effect in the center of Paris due to its restrictive implementation in this area.

Figure 6 presents the change in number of m² for the synthetic region (in red) and for the treated in the central area (in green). We notice a significant rise after 2009 in the treated region, which however experiences a hiatus when the 2011 law is implemented. Between 2012 and 2014, the conversion of HLM in both the counterfactual area and the treated zone appears to progress similarly. After 2014, the pace of in-

crease in the synthetic region seems to decelerate in comparison to the area where the 2014's law has been implemented. In the Online Appendix (16), we present a different strategy where three different synthetic groups are built before each laws, which are then analyzed separatly.

Figure 6: Treated and Control Areas in the Synthetic difference-in-differences in the Core (bandwidth: 600 meters)

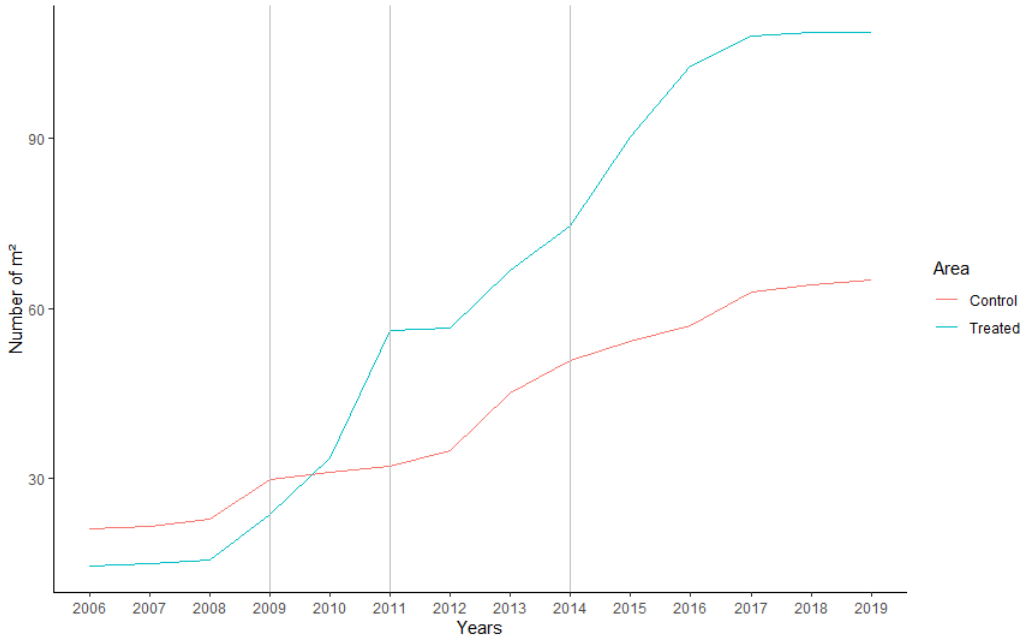


Table 4 presents the SDID results with different bandwidths. Our objective is to assess the distinct spatial impacts of these policies. The 2009 policy, by enforcing a compensation rule within each district, may exert a more substantial influence in the central areas compared to other reforms, mainly because the 2011 and 2014 laws facilitate compensation through HLM situated on the outskirts of the compensation zone. Both of our estimations corroborate this observation, as solely the 2009 law significantly affects social housing construction in central Paris.

This is a second validation of Proposition 1, now for the Core. However, we still have in that case a wide definition of the Core. By reducing this definition, the coefficient first doubles as we approach the center (0.6 in Column 1 compared to 1.2 in Column 2). However, Column 3 (using the MSE optimal bandwidth with an upper limit at 1314, which is even more centered on the center) is not significant. The Online Appendix (12) also shows that once we go beyond the 600 meter threshold, the coefficient starts to lose its significance. This may illustrate that the impact of the

2009 law in the center is however not totally fullfilled or at least not homogeneous accross space. There are certainly some districts in the center where this law has not been effective. It is also possible that we do not have enough observations in these limited areas to reach an interesting conclusion.

Table 4: Social Housing Change from Synthetic Difference in Differences

Treated:	Core				
Bandwidth choice	ad-hoc		MSE-opt	CE-opt	
Bandwidth (in meter)	]300-center]	]600-center]	[1314-center]	[461-center]	
Treated in 2009	0.620**	1.236**	4.783	0.929**	0.830*
	(0.291)	(0.620)	(3.320)	(0.469)	(0.429)
Treated in 2011	0.0567	-0.433	0.909	-0.411	-0.340
	(0.255)	(0.406)	(2.742)	(0.299)	(0.281)
Treated in 2014	-0.184	-0.607	6.506	-0.470	-0.458
	(0.425)	(0.720)	(4.764)	(0.598)	(0.601)
Nb of conversion					0.0081***
					(0.0012)
Income (median)					-0.0006
					(0.0006)
Constant	5.547***	5.719***	5.096***	5.641***	5.871***
	(0.242)	(0.279)	(0.453)	(0.262)	(0.267)
Observations	7,910	7,574	6,930	7,714	7,714
R^2 adj.	0.833	0.847	0.865	0.836	0.843

Notes: . Standard errors are cluster at the neighborhood level in parentheses a: p<0.01, b: p<0.05, c: p<0.1. Results are obtained from a Synthetic difference in differences using the PPML estimator. Column (1) use 300m of bandwidth to the center. Column (2) use 600m bandwidth to the center. Column (3) use the MSE optimal bandwidth. Column (4) and (5) use the Coverage Error (CE) probability neighborhood method. Column (6) and (7) represent high demand neighborhoods. The dependent variable is the number/area of HLM conversions (in m^2). Each estimate includes neighborhood and year fixed effects

We pursue our analysis in Table (5) by focusing of the 2014 law that enables to introduce additionnal controls. We still find that this regulation does not have a discernible effect on the surface of social housing built.

Table 5: Social Housing Change from Synthetic Difference in Differences with added value indicators for schools and Airbnb from 2012 in Paris intra muros

Bandwidth choice	CE-opt [-461,461]				
	Conversion	Income	School AV	Airbnb	FE
Treated in 2014	-0.233	-0.253	-0.273	-0.286	-0.579
	(0.268)	(0.276)	(0.279)	(0.270)	(0.481)
Nb of conversion	0.0206***				0.0065***
	(0.0059)				(0.00201)
Income (median)		-0.0028***			-0.0012
		(0.0010)			(0.0008)
Airbnb				0.0232	-0.0108
				(0.0150)	(0.0108)
Constant	4.777***	5.521***	4.460***	4.621***	7.018***
	(0.333)	(0.403)	(0.435)	(0.379)	(0.256)
School Added Value			✓		✓
Neighborhood FE					✓
Year FE					✓
Observations	4,740	4,740	4,740	4,740	1,518
R^2 adj.	0.0624	0.0873	0.108	0.0483	0.925

Notes: Standard errors are clustered at the neighborhood level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Results are obtained from a Synthetic Difference in Differences using the PPML estimator. All estimations use a triangular distribution of weight with the Coverage Error (CE) probability neighborhood method. The dependent variable is the number/area of HLM conversions (in m²). Column (1) introduces the total number of conversions (in m²), Column (2) includes the median income in each district, Column (3) presents results with indicators of the added value of secondary schools. Performance schools exhibit a positive difference in both access and success rates. Accompanying schools are those where students take longer to obtain their diploma, but where the dropout rate is low. Schools that fall below expectations have poorer results in both success and access rates in comparison to their predicted outcome. Selective schools are characterized by high schools with a high success rate difference and a low access rate difference. Column (4) introduces the Airbnb variables. Column (5) presents results with all these controls. Column (6) incorporates individual fixed effects and time effects.

5 Effects on private housing and social diversity

5.1 Impact on social diversity

The ultimate aim of these laws is to foster social diversity in the city of Paris. We thus analyze here where these laws have had an impact on the spatial distribution of the socio-professional categories of residents.

The data comes from INSEE (National Institute of Statistics and Economic Studies, Classification of Professions and Socio-Professional Categories[18]) for the years 2006 to 2019 in each IRIS neighborhood. We use all the socio-professional categories (without farmers), namely artisans, merchants and business owners; executives and

[18]https://www.insee.fr/en/information/6049871

higher intellectual professions, intermediate professions, employees, workers and finally other individuals without professional activity.

The local entropy index is calculated based on the Theil and Finizza (1971) index and is computed as follows:

$$H = -\frac{\sum_1^{k_i} P_i^k ln P_i^k}{ln k_i},$$

where P_i^k is the share of socio-professional category k in neighborhood i and k_i the number of socio-professional categories present in neighborhood i. This index varies from 0 to 1. The higher the local entropy index, the more heterogeneous the neighborhood is in terms of Socio-Professional Categories representation.

We also delve into the specifics of the French classification of socio-professional categories by directly analyzing, on one hand, the proportion of workers, and on the other, higher intellectual professions (including managers[19]). These two distinct categories have been historically used in labor economics to differentiate between manual occupations and white collar jobs (e.g. Douglas, 1926). They continue to be used as they capture a compelling distinction between occupations that require different levels of education and also provide varying income levels (Goldin and Katz, 2009). We certainly acknowledge that this distinction is less clear than in the past, but it remains useful for characterizing the socio-professional diversity of districts. In addition of the study of the share of these two occupations, we also analyze their location quotient (Isard, 1960) computed as follows:

$$QL = \frac{x_k^i / t_i}{X^k / T},$$

with k the socio-professional category in neighborhood i, x_k^i the number of socio-professional categories present in neighborhood i of the total population in the neighbourhood i represented by t_i related to the number of socio-professional categories present in the whole territoryX^k of the total population in the whole territory T. This index makes it possible to obtain an index of over- or under-representation of the population by neighborhood and by socio-professional category and thus to obtain a relative index. If the index is greater than 1, the socio-professional category

[19]Higher intellectual professions includes executives and managers in business or administration, engineers and other technical professionals, health professionals such as doctors and pharmacists, teaching professionals, including university professors, legal professionals, such as lawyers and judges, and finally artists, authors, journalists, and similar professions.

is over-represented in the neighbourhood compared to the territory as a whole, if the index is less than 1, the socio-professional category is under-represented in the neighbourhood compared to the territory as a whole. These indicators have well known limitations (see Combes et al., 2009) but are still widely used to study residential segregation (e.g. Consolazio et al., 2023).

5.2 Results

In Table (6) we present the effects of these housing regulations on the location choice of the different social-economic categories.

Table 6: Spatial Diversity of Socio-Professional Categories at the Periphery

Type	Higher Intellectual Professions				Workers				Theil Index	
	Location quotient		Share		Location quotient		Share		Total	
Bandwidth (m)	[0-300]		CE		[0-300]		CE		CE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated in 2009	-0.021		-0.027*		0.0015		0.0003		0.0004	
	(0.014)		(0.014)		(0.051)		(0.042)		(0.005)	
Treated in 2011	-0.087***		-0.053***		0.121***		0.038		0.002	
	(0.026)		(0.015)		(0.046)		(0.041)		(0.005)	
Treated in 2014	-0.081**	-0.177***	-0.118***	-0.0466*	0.088	0.129**	0.125**	0.150***	0.005	0.0112
	(0.033)	(0.0511)	(0.020)	(0.0279)	(0.059)	(0.063)	(0.051)	(0.0489)	(0.008)	(0.007)
Nb of conversion	-0.0001	-0.0005	-0.0001	-0.0002	-0.0008	6.92e-05	7e-05	0.0004	0.0001	-7.09e-06
	(0.000)	(0.000)	(0.0002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Income (median)	0.0005**	0.0005**	0.0005***	0.0005***	-0.002***	-0.0026***	-0.002***	-0.0014**	-0.0001***	-0.0001***
	(0.090)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(3.e-05)	(0.000)
Airbnb		-0.0020		-0.0005		-2.82e-05		0.0011		-8.97e-05
		(0.001)		(0.000)		(0.002)		(0.002)		(0.000)
Constant	0.314***	0.430***	-0.885***	-0.913***	-0.413***	-0.238	-2.525***	-2.667***	-0.183***	-0.192***
	(0.090)	(0.104)	(0.060)	(0.066)	(0.122)	(0.272)	(0.129)	(0.241)	(0.0115)	(0.019)
School added value		✓		✓		✓		✓		✓
Neighborhood FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,7876	8,442	33,558	9,408	32,634	6,589	28,800	5,976	31,486	6,120
R^2 adj.	0.910	0.809	0.932	0.841	0.819	0.773	0.777	0.759	0.739	0.816

Notes: Standard errors are cluster at the neighborhood level in parentheses [a] p<0.01, [b] p<0.05, [c] p<0.1. Results are obtained from a Synthetic difference in differences using the OLS estimator. Columns (1) and (2) represent managers location quotient and use 300m bandwidth at the periphery. Columns (3) and (4) represent managers share and use the Coverage Error (CE) probability neighborhood method. Columns (5) and (6) represent workers location quotient and use 300m bandwidth at the periphery. Columns (7) and (8) represent workers share and use the Coverage Error (CE) probability neighborhood method. Columns (9) and (10) represent Theil index and use the Coverage Error (CE) probability neighborhood method.

By utilizing the SDID at the border, we observed that these laws have resulted in a decrease in the proportion of high intellectual profession both in relative terms and in absolute term (Column 1 and 3). However, the outcomes are less definitive concerning workers, as the coefficients are mostly not significant. Only the 2011 law, at the immediate proximity of the border (300 meters) is significant (Column 5).[20] However, if we include the number of short-term rentals and the indicator of school added value only for Paris intra-muros and from 2012 onwards, the coefficient appears significant after 2014 (Column 6). The final column for all categories and laws (Column 9), employing the Theil index, indicates that these laws have not significantly contributed to reduce spatial inequality in occupation.[21]

In Table (7), we present the same estimate but for the city center. We get similar results, these laws have a significant negative effect on the proportion of higher intellectual professions, but no effect on the proportion of workers and overall we cannot reject the null hypothesis of no effect on social diversity. Except for workers share in Paris intra-muros from 2012 after the 2014 law, but which is only significant at the 10% level.

[20] Not reported here we test with a bandwith at 600 and the coefficient is no longer significant.

[21] Although not presented here, we conducted estimations using the difference-in-discontinuity estimator and obtained similar findings (consistently negative and significant for managers, but not significant for workers and for the total).

Table 7: Diversity in the Center

Type	Managers				Workers				Theil Index	
	Location quotient		Share		Location quotient		Share		Total	
Bandwidth (in meter)	[0-300]		CE		[0-300]		CE		CE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated in 2009	-0.038***		-0.036**		0.030		0.069		0.003	
	(0.01)		(0.016)		(0.040)		(0.052)		(0.007)	
Treated in 2011	-0.072***		-0.071***		0.072*		0.0441		0.011	
	(0.015)		(0.015)		(0.042)		(0.064)		(0.008)	
Treated in 2014	-0.040***	-0.171***	-0.062***	-0.0385*	0.006	0.0432	0.0933	0.123*	-0.005	0.0004
	(0.015)	(0.0456)	(0.017)	(0.020)	(0.05)	(0.0529)	(0.07)	(0.065)	(0.008)	(0.007)
Nb of conversion	-0.0002	-0.0004	-0.0003	-0.0003	1e-05	-0.0007	-0.0002	-0.0004	0.0001	0.0002*
	(0.000)	(0.000)	(0.0002)	(0.000)	(0.000)	(0.001)	(0.0002)	(0.001)	(9e-05)	(0.000)
Income (median)	2.e-05	2.08e-05	-5e-06	-9.56e-06	0.0002	0.0002	0.0002	2.20e-05	1e-05	-3.18e-05
	(5e-05)	(0.000)	(6e-05)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(2e-05)	(0.000)
Airbnb		-0.0002		-0.0002		0.0003		0.0016		0.0002
		(0.001)		(0.001)		(0.002)		(0.002)		(0.000)
Constant	0.66***	0.682***	-0.66***	-0.683***	-1.34***	-1.340***	-3.29***	-3.246***	-0.24***	-0.229***
	(0.02)	(0.033)	(0.021)	(0.021)	(0.075)	(0.0810)	(0.074)	(0.103)	(0.008)	(0.0109)
School added value		✓		✓		✓		✓		✓
Neighborhood FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	30,084	11,018	34,244	10,094	35,000	8,448	29,352	6,390	32,019	6,489
R^2 adj.	0.828	0.717	0.898	0.736	0.577	0.659	0.678	0.737	0.703	0.802

Notes: Standard errors are cluster at the neighborhood level in parentheses ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1. Results are obtained from a Synthetic difference in differences using the OLS estimator. Columns (1) and (2) represent managers location quotient and use 300m bandwidth to the center inner compensation zone. Columns (3) and (4) represent managers share and use the Coverage Error (CE) probability neighborhood method. Columns (5) and (6) represent workers location quotient and use 300m bandwidth to the center inner compensation zone. Columns (7) and (8) represent workers share and use the Coverage Error (CE) probability neighborhood method. Columns (9) and (10) represent Theil index and use the Coverage Error (CE) probability neighborhood method.

To complete the analysis of inequality, regressions are run again with the inter-decile ratio, i.e. the richest 10% over the poorest 10% of the population, as the dependent variable. Using the SDID method, we find that income inequality between the extreme incomes of each neighborhood tends to decrease at the border the reinforced area in 2014 but with a low certainty (Column 1, Tab 8) which is not significant in other estimation (Column 2, 3, 4).

Table 8: Inter-decile index

Type	Periphery		Core	
Bandwidth (in meter)	[0-300]		[300-center]	
Treated in 2009	0.013		0.0195	
	(0.014)		(0.0134)	
Treated in 2011	-0.0006		-0.00768	
	(0.013)		(0.0258)	
Treated in 2014	0.027*	0.0091	0.0231	-0.0093
	(0.015)	(0.017)	(0.0219)	(0.012)
Nb of conversion	-0.0004	-0.0003	-0.0006**	-0.0003
	(0.0004)	(0.001)	(0.0002)	(0.000)
Income (median)	-0.002***	-0.0013***	-0.0016***	-0.0011***
	(0.0002)	(0.000)	(0.000176)	(0.000)
Airbnb		0.0004		0.0002
		(0.001)		(0.001)
Constant	2.83***	2.741***	2.90***	2.783***
	(0.079)	(0.105)	(0.0716)	(0.078)
School added value		✓		✓
Neighborhood FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	29,876	6,094	31,654	7,491
R^2 adj.	0.918	0.931	0.932	0.945

Notes: Standard errors are cluster at the neighborhood level in parentheses [a] p<0.01, [b] p<0.05, [c] p<0.1. Results are obtained from a Synthetic difference in differences using the OLS estimator. Columns (1) and (2) use 300m bandwidth at the periphery with Decile9/Decile1 as dependant variable.

6 Conclusion

To paraphrase Hirschman (1970), the silent exit of the working class from inner cities has accompagned the price increase in many global cities. In some places, voices of

opposition to gentrification have been raised[22] and several local policies have been implemented. In this study, we examine three successive laws implemented in 2009, 2011, and 2014 that promote the conversion of offices and other commercial premises into private or social housing. A certain amount of trial and error can be observed in the policy imposed by these laws. The 2009 law was enacted in the particular political context of the 2008 re-election campaign of a socialist candidate. Although this law was not explicitly a promise, it can be viewed as the main tool to fulfill the commitment to provide more than 40,000 social housing units in the capital, including in the center of Paris, between 2008 and 2014. Perhaps this regulation appeared too restrictive after its enforcement, or, in the absence of any assessment, it was considered ineffective. Regardless of the reason, the 2011 law completely relaxed the district compensation constraint. Finally, the 2014 law has represented a compromise that remains in effect today.

Our analysis shows that the 2009 law did, in fact, significantly encourage the redevelopment of social housing in the city center while the 2011 and 2014 laws present a reversed picture for social housing, showing significant effects at the border of the compensation area but not in the city center. Our analysis thus demonstrates that the stipulations regarding where redevelopment is permitted can significantly shape the distribution of social housing. By incorporating various controls as well as fixed effects, we further demonstrate that in areas where these laws had a significant impact, they constituted a first-order effect of redevelopment towards social housing. We further reinforced this interpretation through various robustness checks using different estimators and control groups. However, the fact that the most recent laws only have an effect on districts located in the periphery, which is a relatively small area, and not in the broadly defined center, signifies a failure of these regulations in terms of their primary objective. This is all the more worrying as the 2014 law seems to have, at best no effect. We reinforce this interpretation by finding a lack of impact from these redevelopments on the Theil's index of social diversity.

Although our analysis presents an internal validity, it obviously lacks the external one. More research needs to be conducted in various cities and across different periods to gain a deeper understanding of how redevelopment influences the spatial

[22]The YIMBY movement in particular has organized several demonstrations in California to protest against areas significantly disrupted by rapid gentrification. In France, the "Yellow Vest" movement has also been driven by individuals considering that they have been excluded from the economic prosperity of metropolitan areas. See Brown-Saracino (2017) which surveys the literature in sociology that analyzes the public resistance to gentrification.

and social fabric of cities.

7 References

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8 Appendix : school value added

The added value indicators cover 4,300 schools with very different characteristics, particularly in terms of student profiles. They are build along two dimensions. First, the rate of success which is the ratio between the number of students who passed the exam and the number of students who took it. Second, the access rate which evaluates the probability that a student will graduate at the end of a school career spent entirely in one high school, even if he or she has repeated a year.

From this computation, the statistics department of the French Ministry of Education, hereafter DEPP (Direction de l'Evaluation, de la Prospective et de la Performance) categorize schools according to their added value in terms of success and access.

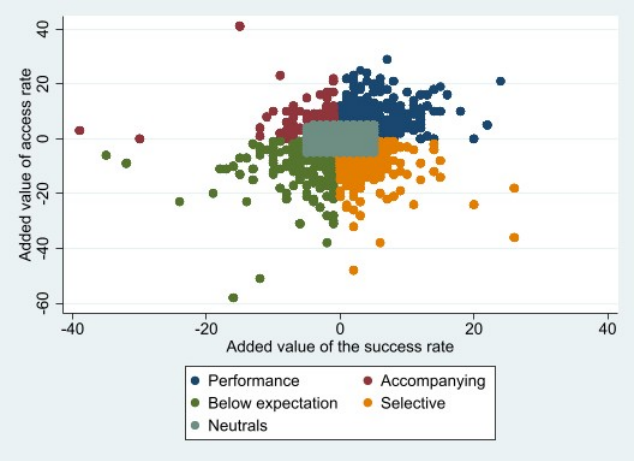
Schools can then be classified as "neutral", "performance", "accompanying", "below expectation" and "selective". Figure 7 represents these different categories along the success rate on the horizontal axis and the access rate on the vertical axis.

The neutrals contribute neither more, nor less, to the success of their students than the average of high schools that are similar in terms of student profiles. They are also similar to the average in term of access. The accompanying ones, are schools where students take longer time to obtain their high school diploma, but who have lower dropout rates. The below expectations ones, have poorer results both in terms of success and access considering the profile of their students. The performance

schools, correspond to high schools with a wide positive gap in both access and success rates. The selective schools correspond to high schools with a high success rate gap and a low access rate gap.

Since the methodology has changed over time, we cannot use the data from the start of our period. We limit our analysis to 2012 when considering these data. We select the nearest secondary school for each neighborhood.[23]

Figure 7: Secondary schools categories



9 Appendix: synthetic of the periphery

Method

We reproduce here the same analysis than the one presented in Section 3 concerning the Periphery but we change the control group, which is now a synthetic area of the treated one. This analysis is thus a robustness check, we replace here the Diff-in-Disc estimation presented in the text by a Synthetic Diff-in-diff (SDID) estimation.

Based on the assumption that in the absence of the treatment, the treated unit and the synthetic control group would have followed parallel trends over time, the SDID helps to mitigate the bias of the Diff-in-Disc method presented in the text. The similarity of the control group is indeed always debatable in spatial Diff-in-Disc and the SDID provides a good alternative.

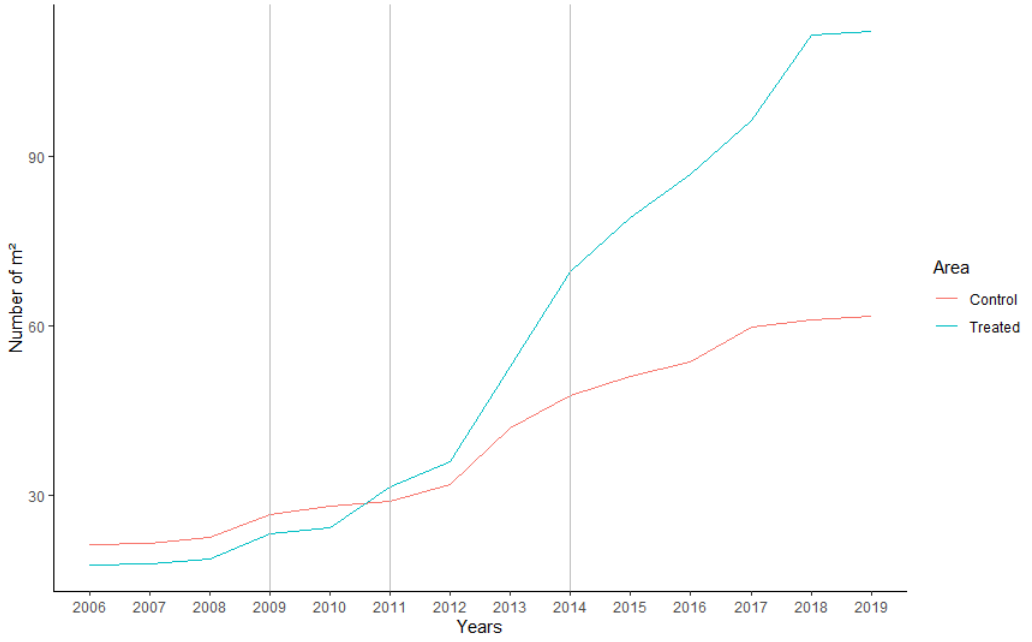
[23] Estimates have been made for various indices. An index taking into account the added value of the access rate and a Baccalauréat success rate of more than 90% and an index taking into account the success rate of more than 90% and the access rate of more than 70% (average values for all secondary schools). The results are similar.

We conducted a series of estimations by considering the same set of treated districts than in the section with the Diff-in-Disc for the Periphery, namely with distance from the border of the reinforced area using the different bandwidth already presented. The aim is to provide results that are directly comparable with those presented until now.

The control zone obviously differs from the Diff-in-Disc by constructing a synthetic area using untreated observations located beyond the border. To provide a visual example, the treated are still represented by the dark grey area of the Map 3, while the untreated are selected in the bright gray area of the Map 5.

Figure (8) illustrates change in the conversion of HLM (in m^2) for the synthetic area and for the districts where the different laws have been applied. We observe a clear divergence between the two group after 2010, which increases over time.

Figure 8: Treated and Control Areas in the Synthetic difference-in-differences at the border (bandwidth: 600 meters)



Results

Table 9 presents the results of the synthetic difference-in-differences analysis, taking into account different distances from the edge of the compensation zone. Our findings reveal similar outcomes than the one presented in the text with a different

method, the 2009 law demonstrating no significant effect, while the 2011 and 2014 reforms successfully promoted the construction of social housing. [24]

Table 9: Social Housing Change at the Periphery

Treated:	Border				
Bandwidth choice	ad-hoc		MSE-opt	CE-opt	
Bandwidth (in meter)	[0-300]	[0-600]	[0-1314]	[0-461]	[0-461]
Treated in 2009	0.153	0.0632	0.123	0.107	0.0443
	(0.195)	(0.156)	(0.176)	(0.147)	(0.148)
Treated in 2011	0.534	0.499*	0.400*	0.412	0.437
	(0.381)	(0.289)	(0.204)	(0.322)	(0.307)
Treated in 2014	0.479**	0.467**	0.426***	0.505**	0.443**
	(0.227)	(0.188)	(0.143)	(0.201)	(0.195)
Number of conversion					0.0079***
					(0.0022)
Median income (/100)					-0.0019
					(0.00358)
Constant	5.320***	5.146***	5.500***	5.199***	5.79***
	(0.228)	(0.199)	(0.199)	(0.213)	(1.084)
Observations	7,378	7,714	8,358	7,574	7,574
R^2 adj.	0.776	0.760	0.820	0.780	0.785

Notes: Standard errors are cluster at the neighborhood level in parentheses a: p<0.01, b: p<0.05, c: p<0.1. Results are obtained from a Synthetic difference in differences using the PPML estimator. Column (1) use 300m bandwidth. Column (2) use 600m bandwidth. Column (3) use the Coverage Error (CE) probability neighborhood method. Columns (4) and (5) use the MSE optimal bandwidth. The dependent variable is the number/area of HLM conversions (in m^2). Each estimate includes neighborhood and year fixed effects

The inclusion of additional controls in the last Column of Table (9) and in Table (10) that concerns only the 2014 reform (due to data limitation regarding controls) have hardly any effect on the coefficient estimated. To conclude, we verify here the main result obtained so far, only the 2011 and 2014 laws have significantly fostered the conversion of buildings/offices in social housing at the border of the treated area.

[24] See Online Appendix (16, Column 1-3) for estimates with one single treatment

Table 10: Social Housing Change from Synthetic difference-in-differences with added value indicators for schools and Airbnb from 2012 in Paris intra muros

Bandwidth choice	CE-opt [-461,461]				
	Conversion	Income	School AV	Airbnb	FE
Treated in 2014	0.370*	0.377**	0.401**	0.366**	0.335*
	(0.204)	(0.183)	(0.192)	(0.185)	(0.179)
Nb of conversion	0.0429***				0.0120***
	(0.0077)				(0.0045)
Income (median)		-0.0024**			-0.0045***
		(0.0009)			(0.0045)
Airbnb				0.0199*	0.0108
				(0.0119)	(0.00897)
Constant	4.884***	5.697***	5.266***	4.925***	7.096***
	(0.327)	(0.395)	(0.354)	(0.360)	(0.781)
School Added Value			✓		✓
Neighborhood FE					✓
Year FE					✓
Observations	4158	4158	4158	4158	1452
R^2 adj.	0.0847	0.0610	0.0404	0.0416	0.868

Notes: Standard errors are clustered at the neighborhood level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Results are obtained from a Synthetic difference-in-differences using the PPML estimator. All estimations use a triangular distribution of weight with the Coverage Error (CE) probability neighborhood method. The dependent variable is the number/area of HLM conversions (in m²). Column (1) introduces the total number of conversions (in m²), Column (2) includes the median income in each district, Column (3) presents results with indicators of the added value of secondary schools. Column (4) introduces the Airbnb variables. Column (5) presents results with all these controls. Column (6) incorporates individual fixed effects and time effects. Since indicators of added value of secondary schools are not significant when fixed effects are introduced in Column (5), they are not reported here.

10 Online Appendix (not for publication): a Stylized Model

We present here a stylized model similar to Garcia-López et al. (2020) to separate the drivers of supply and demand in property conversion. In this model, property redevelopment developers choose to market their converted homes either to individual households or social landlords. A testable outcome of this model is that these laws increase the long-term supply of social housing, contingent on several factors. In particular, an increase in household income, a decline in state investment in social housing, or a reluctance among households to reside in areas with social housings, counteracts the regulation by diminishing the long-term demand for social housing. This model also illustrates that the costs to compensation tend to be higher in areas with high tension. This model is not integrate in the text since it oversimplifies the ef-

fects of the different laws. In particular, the trade-off to invest at the Periphery of the compensation zone or at the Core that changes with the different laws (as discussed on Proposition 1 and 2) is not introduced in this analysis. The model is nevertheless useful to discuss the supply of conversion and also to pinpoint demand shifters that should be controled in the empirical section.

Applicants for conversion, hereafter called Property Redevelopment Developers (PRD), aim to sell their goods at a price p_g to social landlords or at a price p_h to high/middle-income households (more precisely to households with an income too high to benefit from social housing), hereafter called "households". We consider two different areas: the compensation zone, named the center or the core, represented by a superscript c, and the rest of the city, the suburb or the periphery, labeled by an upper script p.

Each PRD faces a cost κ to convert its building. Since the "2:1 rule" implies that a PRD has to pay twice as much compensation titles for private housing[25] than for social housing in the center of the city, this law implies a comparision between $p_h - 2\kappa$ and $p_p - \kappa$. This cost of conversion κ can be magnified (or reduced) depending on the spatial constraint of the law. The regulation can indeed be very restrictive by requiring the doubling of the surface area in the same district, less restrictive by imposing at least 50% in the district, or not very restrictive by enabling the applicant to compensate elsewhere.[26] As explained earlier, the compensation rates tend to be higher in areas with high tension. Therefore, the requirement to provide compensation in the same district makes this regulation much more restrictive there than in other places.

Furthermore, we assume that past regulations concerning social housing involve several additional costs that vary from one PRD to another. These heterogeneous costs are denoted β_n for each developer, n, that converts an unit in social housing.

At the equilibrium, there is a marginal PRD who is indifferent between selling to

[25] In fact, the PRD first redevelops housing into offices and then has to double the surface of private housing, we take a short-cut here by not mentionning the intermediate step concerning offices/commercial premises redevelopment.

[26] The current model presents only one part of the mechanism, indeed, the compensation title κ which act as a production tax for the PRD is somewhat like a subvention for the specialized entities that sell these titles. Hence an increase in the restrictiveness of the law may, in a second step, reduce the demand of κ and then the production of social housing by the seller of these titles. Adding this second step, however, could make the presentation more cumbersome without adding much clarity.

an household or to a social landlord at:[27]

$$p_h^c - p_g^c = \kappa - \beta_n^*. \tag{2}$$

PRD with $\beta_n < \beta_n^*$ convert their goods to social housing, while those with $\beta_n > \beta_n^*$ convert to private housing.

The indirect utility of an household h that has chosen its optimal private housing in the neighborhood c is $V_h^c = Y - p_h^c - \alpha \mathbb{P}(\beta_n) + e_h^c$, where Y is its (exogeneous) income while $\alpha \mathbb{P}(\beta_n)$ represents a negative externality which increases in the number of premises converted in social housing in this neighborhood. This externality can be explained by an homophily in social preferences that leads these individuals to prefer environment with people sharing the same level of income (Currarini et al., 2009), or due to an insecurity feeling in disadvantaged areas, or to the bad reputation of schools there.[28]

Finally, this household has a choice to live in the center or at the periphery with e_h^c the idiosyncratic preference to live in the center.

We denoted $\overline{V_h^p}$ the indirect utility of the household in p. By comparing these two levels of welfare, the marginal household that chose to live in c proposes the following price:

$$p_h^c = Y - \alpha \mathbb{P}(\beta_n^*) + e_h^* - \overline{V_h^p}. \tag{3}$$

All the households with $e_h > e_h^*$ lives in the center, while other are at the periphery.

The indirect utility that a social landlord gets in c is $V_g^c = G - p_g + e_g$ where G is the public good or service provided to low-income individuals. Indeed, the primary objective of the social landlord, as established by law, is to provide good-quality housing for low-income and disadvantaged individuals. e_g is its idiosyncratic preference to acquire a unit in c. $\overline{V_g^p}$ is its indirect utility at the periphery. The price

[27] With $\kappa > \beta_n$ the price of private housing is higher than the price of social housing. There are many evidences of this, for instance a French real estate developer declared in 2013 that the different regulations imply that "the developer finds themselves obliged to raise the price for private buyers who, as a result, largely finance social housing".

[28] There is indeed some evidence about a link between territorial stigmatization and schools. In particular, Garrouste and Lafourcade (2022) carefully identify how a zoning reform in France, that signals the poverty of the neighborhood, has triggered a drop in pupil enrollment from parents that avoides the public schools in this policy area. This "zone-and-shame" effect, in part illustrates what the aversion to live near HLM, α, may be.

proposed by the marginal social landlord is then given by:

$$p_g^c = G + e_g^* - \overline{V_g^p}. \tag{4}$$

Social landlords with $e_g > e_g^*$ invest in the center, while other are at the periphery.

Finally we assume that β_n, e_h and e_g follow a normal distribution on the support [0,1], such as $1 - e_h^*$ and $1 - e_g^*$ are the shares of residents and social landlord that invest in c. With C the number of unit converted, we have $C\beta_n^* = 1 - e_g^*$ such as the supply of social housing equals the demand, while market clearing for private housing gives $C(1 - \beta_n^*) = 1 - e_h^*$.

Inserting (3) and (4) in (2), and using the market clearing condition gives:

$$\beta_n^* = \frac{\kappa + G - Y + C + \overline{V_h^p} - \overline{V_g^s}}{1 - \alpha + 2C} \tag{5}$$

This expression shows that an increase in the restrictiveness of the law κ, foster an eviction effect from private housing to social one. Then the first proposition of this model is that the three laws of 2009, 2011, and 2012 should have resulted in an increase in the number of social housing.

This equation also indicates that the share of HLM increases with the aversion of household to social mixity α. An increase in the concentration of social housing in a particular location deter households from settling there, which in turn, automatically elevates the proportion of social housing.

An increase in the income of households Y also reduces the share of social housing. This result matters for the empirical analysis, since our period of analysis is characterized by successive variation in income.[29] Not modelled here a change in the market potential of districts, may also have a similar role than Y_r, abeit with multiple additional effects (See Redding, 2023 for a survey).[30]

[29]For instance, the financial crisis of 2007-08 has led to a fall of income that might have affected the demand of household in the districts. In contrast, the rise of income in central Paris over the period 2010-2018 may have play a central role by contradicting the effect of the law.

[30]In that case the mechanism may play as follows, an increase in the number of firms in one location, directly reduce the supply of converted unit and increase the price of land, but also indirectly increase the potential number of resident for a given supply of floor space. This, in turn, bids up the price for residential floor space, which reduces the expected utility to convert a premise in HLM. If firms operates under increasing returns or benefit of technological spillovers, agglomeration economies are likely, and then may increase the wage of residents pushing social housing elsewhere *via* Y_r.

An higher effort of landlord to provide good-quality housing G, fosters the share of social housing. An higher effort of the central and/or local government to stimulate the investment in social housing, or to reduce the risk of investment for the PDR[31] can also be understood via an increase in G.

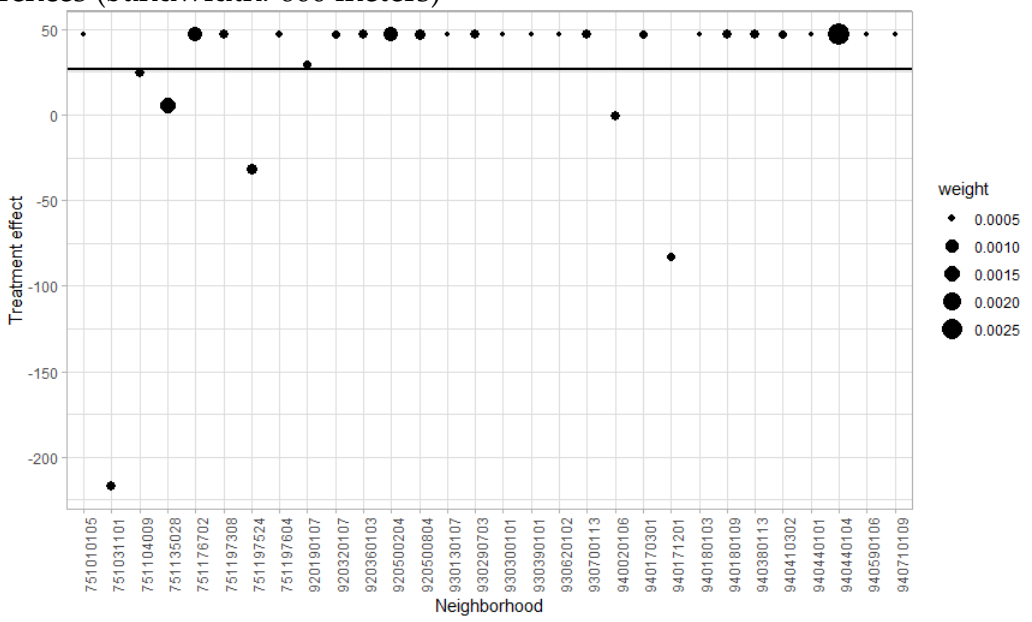
Finally, β_n is a decreasing function of the stock of unit, C, that are converted. When there is a high number of converted housing, the law is less bidding for conversion toward private housing. The larger the number of units, the easier it is to comply with the legal rule of doubling the surface when converting on office into a private housing. This can have an impact that differ from one law to another. Indeed the rule to compensate in the same district in 2009, makes this law more difficult to implement in the center due to the limited stock of conversion available.

11 Online Appendix (not for publication): Size of Weights

The weights used to build the synthetic controls are presented in Figure 9 and present relatively few extreme values.

[31] For instance in France, the 2000 law on urban solidarity and renewal (SRU) has allowed landlord to directly buy housing from real estate developer before the construction (called "ventes en état futur d'achèvement"). This has been a powerful mechanism by which real estate developers have secured their investment for private housing. Indeed the buying of entire block by social landlord, before the construction, reduces the credit rationing of PDR by banks in period of recession.

Figure 9: Weights of the top 30 neighborhoods in the Synthetic Difference-in-Differences (bandwidth: 600 meters)



12 Online Appendix (not for publication): Robustness check concerning the bandwith choices

Table (11) provides the main results of the Diff-in-Disc for the different bandwidths. Table (12) the estimation at the periphery with the SDID and (13) at the center.

Table 11: Difference in Discontinuity of Social Housing Change - Triangular weights

Bandwidth	300	400	500	600	700	800	900
Treated in 2009	0.240	0.222	0.192	0.144	0.0969	0.0836	0.0367
	(0.184)	(0.173)	(0.157)	(0.146)	(0.142)	(0.144)	(0.146)
Treated in 2011	0.665*	0.647*	0.626*	0.658**	0.657**	0.641**	0.657***
	(0.390)	(0.370)	(0.347)	(0.322)	(0.292)	(0.269)	(0.252)
Treated in 2014	0.460*	0.492**	0.527**	0.545**	0.533**	0.514***	0.519***
	(0.244)	(0.238)	(0.230)	(0.221)	(0.210))	((0.199)	(0.190)
Constant	6.879***	6.773***	6.689***	6.592***	6.552***	6.549***	6.520***
	(0.0742)	(0.0926)	(0.104)	(0.114)	(0.114)	(0.121)	(0.128)
Observations	1,568	1,792	2,100	2,352	2,660	2,912	3,234
Pseudo-R2	0.9080	0.9027	0.8987	0.8948	0.8905	0.8865	0.8837
Neighborhood FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses; a p<0.01, b p<0.05, c p<0.1

Table 12: Difference in Differences of Social Housing Change - Periphery Estimation

Bandwidth	300	400	500	600	700	800	900
Treated in 2009	0.153	0.157	0.119	0.0632	0.0373	0.0925	-0.0306
	(0.195)	(0.167)	(0.150)	(0.156)	(0.162)	(0.150)	(0.199)
Treated in 2011	0.534	0.449	0.436	0.499*	0.440*	0.453*	0.550**
	(0.381)	(0.354)	(0.318)	(0.289)	(0.255)	(0.246)	(0.220)
Treated in 2014	0.479**	0.440**	0.514***	0.467**	0.405**	0.412**	0.402**
	(0.227)	(0.219)	(0.198)	(0.188)	(0.173)	(0.166)	(0.158)
Constant	5.320***	5.249***	5.186***	5.146***	5.146***	5.279***	5.439***
	(0.228)	(0.226)	(0.210)	(0.199)	(0.198)	(0.191)	(0.185)
Observations	7,378	7,462	7,616	7,714	7,826	7,924	8,106
Pseudo-R2	0.776	0.780	0.778	0.760	0.773	0.785	0.807
Neighborhood FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses; a p<0.01, b p<0.05, c p<0.1

Table 13: Difference in Differences of Social Housing Change - Core Estimation

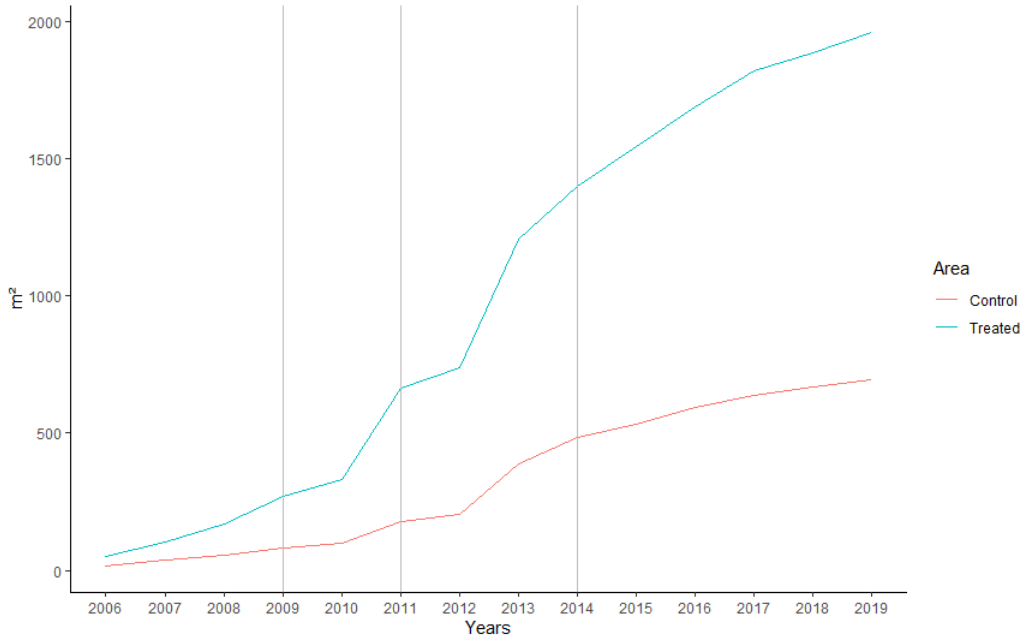
Bandwidth	300	400	500	600	700	800	900
Treated in 2009	0.620**	0.737**	1.065**	1.236**	1.376	2.794**	3.109
	(0.291)	(0.364)	(0.486)	(0.620)	(0.898)	(1.388)	(2.420)
Treated in 2011	0.0567	-0.128	-0.426	-0.433	-0.931*	-1.551***	-0.620
	(0.255)	(0.284)	(0.318)	(0.406)	(0.529)	(0.583)	(0.855)
Treated in 2014	-0.184	-0.431	-0.454	-0.607	-1.065	-1.466	-2.427*
	(0.425)	(0.488)	(0.628)	(0.720)	(0.904)	(1.092)	(1.434)
Constant	5.547***	5.590***	5.655***	5.719***	5.788***	5.733***	5.580***
	(0.242)	(0.250)	(0.265)	(0.279)	(0.294)	(0.333)	(0.462)
Observations	7,910	7,826	7,672	7,574	7,462	7,364	7,182
Pseudo-R2	0.833	0.835	0.836	0.847	0.853	0.857	0.857
Neighborhood FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses; a $p<0.01$, b $p<0.05$, c $p<0.1$

13 Online Appendix (not for publication): Without Parallel Trends, No Estimations

In Section 5 we do not lead again the diff-in-disc estimation since pre-trend are rather unconvincing as illustrated by Figure 10.

Figure 10: Treated and Control Areas in the Difference-in discontinuities for private housing change (bandwidth: 600 meters)



14 Online Appendix (not for publication): No Zero but OLS

As argued in the text, we use the PPML estimators since the analysis of districts with no redevelopment is particularly important for understanding the effects of these laws. However, one may want to compare the results without these zeroes and with the OLS estimator. In Table (14), we confirm the results for the 2009 law, which is significant in the center but not at the border. We also find results consistent with those presented in the text for the 2014 law, which encourages the redevelopment of social housing at the periphery but not in the core.

Table 14: OLS Estimations

Dependent variable	Social Housing Change		
Bandwidth (in meter)	[0-600]		]600-center]
	Difference in Discontinuity	Synthetic difference-in-differences	
	(1)	(2)	(3)
Treated in 2009	0.253	-0.712	75.26**
	(5.095)	(4.847)	(34.91)
Treated in 2011	24.85	17.98	31.31
	(15.51)	(13.38)	(24.17)
Treated in 2014	49.02*	49.15**	45.90
	(28.11)	(24.14)	(28.70)
Constant	73.39***	42.44***	41.19***
	(5.377)	(7.129)	(13.20)
Observations	6,678	34,776	35,238
R^2 adj.	0.95	0.63	0.64

Notes: Standard errors are cluster at the neighborhood level in parentheses [a] p<0.01, [b] p<0.05, [c] p<0.1. Results are obtained from a Synthetic difference in differences and Difference in Discontinuity using the OLS estimator. Columns (1) use 600m bandwidth and represent social housing change from Difference in Discontinuity. Columns (2) use 600m bandwidth and represent social housing change from Synthetic difference-in-differences. Column (3) use 600m bandwidth to the center and represent social housing change from Synthetic difference-in-differences. Each estimate includes neighborhood and year fixed effects.

15 Online Appendix (not for publication): Non-Parametric Synthetic Control Method

The computation of weights in synthetic control methods are based on different techniques that have been discussed a lot in the literature (Abadie and Gardeazabal, 2003; Abadie et al., 2010, Arkhangelsky et al., 2021). We present here graphics of the change in redevelopment of social housing for the treated and control groups using these alternative methods as well as the method presented in the text. We use in particular the nonparametric synthetic control method developed by Cerulli (2020). This technique uses a kernel function with a pre-defined bandwidth to calculate counterfactual weights. The bandwidth is chosen to minimize the root mean-squared prediction error (RMSPE). Let's take the example of the analysis at the periphery (600m from the compensation border). Figure 11 indicates an optimum bandwidth of 1 which is then the optimal vector distance (Mahalanobis distance) between treated units and controls within the bandwidth. Figure 12 shows the results of the coun-

terfactuals generated with the non-parametric method, with prediction errors, because the treated and the control have a time lag, they should merge perfectly. In contrast, the synthetic control method minimizes the prediction error between the treated and the series generated by a linear regression of the same variables for the control units (see Figure Synthetic control method), the counterfactual appears to follow the treated observations in the pre-processing period. Finally, Figure Synthetic difference-in-differences method shows the synthetic difference-in-differences method chosen in our analysis. We can both observe how the treated and control observations are parallel in the pre-treatment period, and how the control group is not affected by the treatment.

Figure 11: Optimal bandwidth for the non-parametric synthetic control method

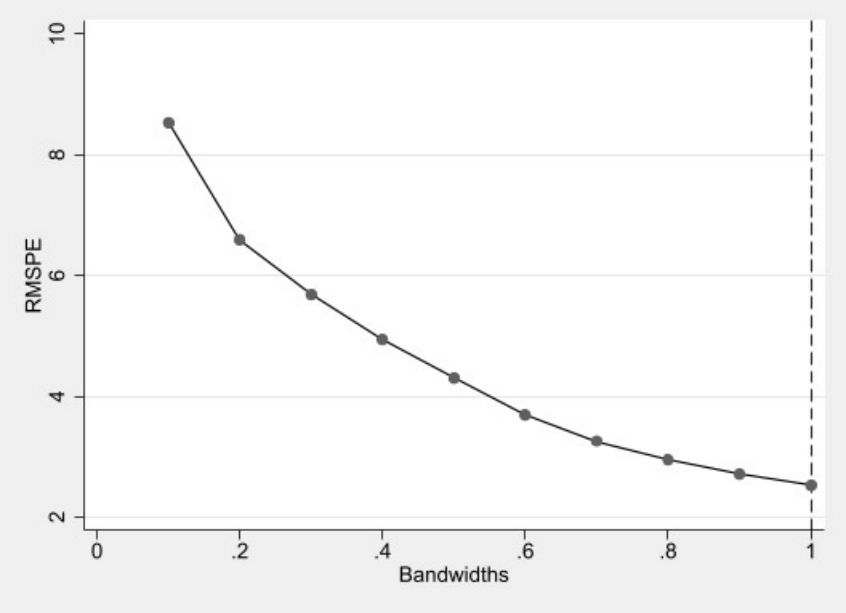


Figure 12: Non-parametric synthetic control method

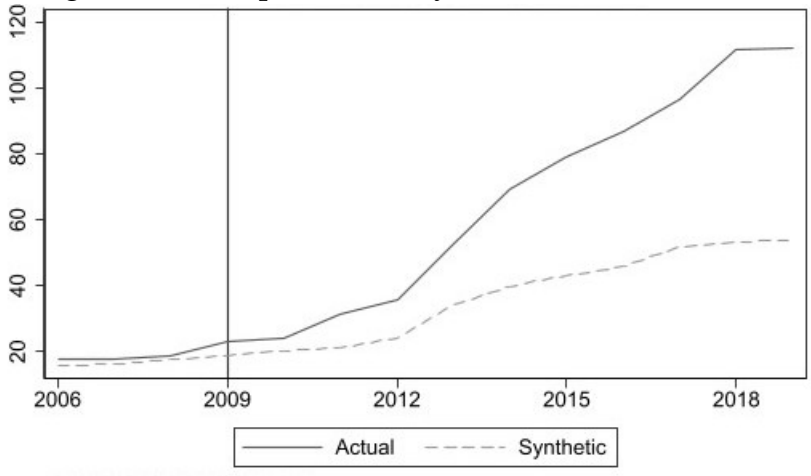


Figure 13: Synthetic control method

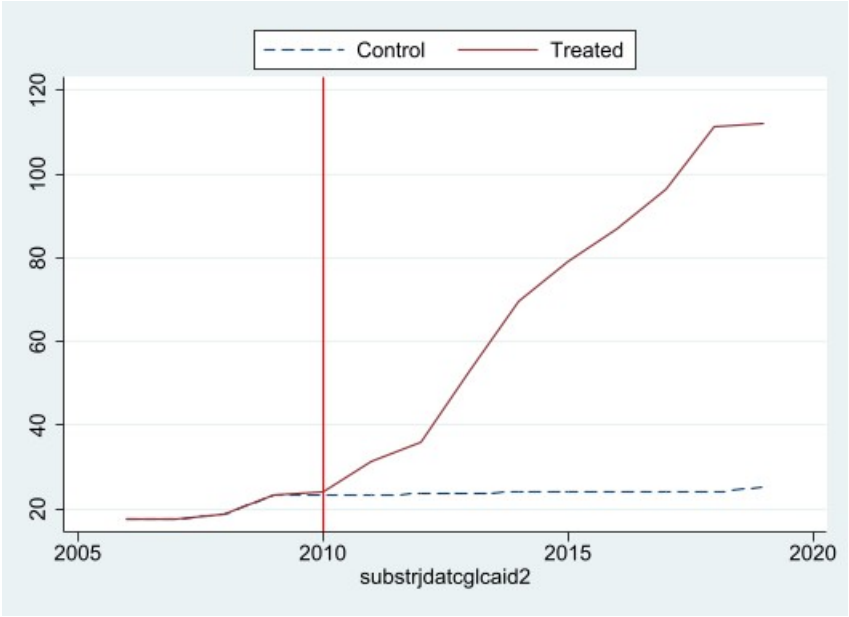
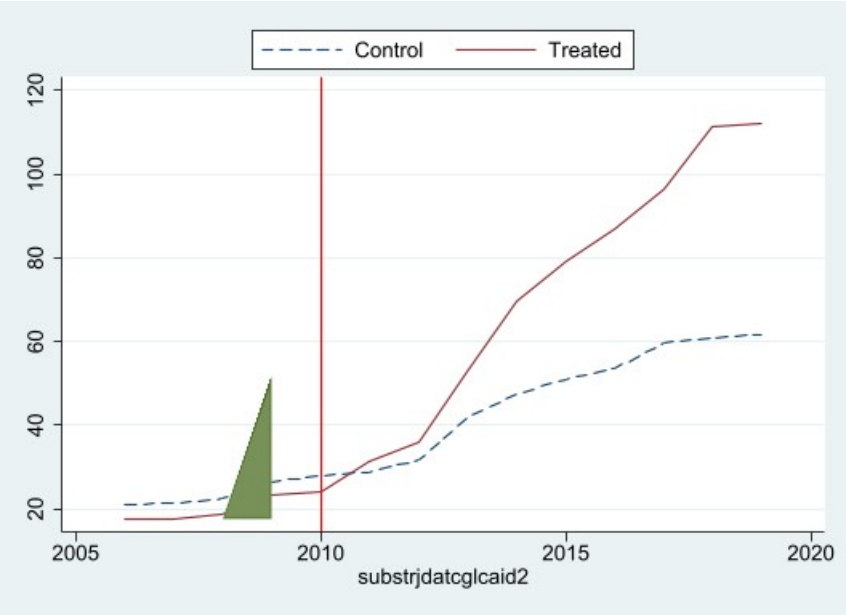


Figure 14: Synthetic difference-in-differences method



16 Online Appendix (not for publication): One Single Treatment by Estimation

Table (15) presents estimates based on a single year of treatment at both the periphery and center of the reinforcement zone, using the synthetic difference method. Weights are adjusted for the treatment date, and all other post-treatment years are excluded. For example, when the treatment year is 2009, weights are adjusted before 2009 and the treatment period ends in 2011, which is the year of the second treatment. The results are consistent with the results presented in the text when treatment periods are examined individually for social and private housing change.

Table 15: Synthetic difference-in-differences with one treatment and placebo test for Differences-in-discontinuities

Dependent variable	Social Housing Change					
Bandwidth (in meter)	[0-461]			]461-center]		
	Synthetic difference-in-differences					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated in 2009	0.043			0.665*		
	(0.14)			(0.439)		
Treated in 2011		0.423			-0.099	
		(0.302)			(0.372)	
Treated in 2014			0.481*			-0.395
			(0.304)			(0.628)
Nb of conversion	0.01***	0.03***	0.005***	0.02***	0.019***	0.008***
	(0.003)	(0.004)	(0.002)	(0.006)	(0.002)	(0.001)
Income (median)	0.006	-0.001	-0.002	-0.014	-0.0013*	-0.000
	(0.000)	(0.005)	(0.003)	(0.009)	(0.000)	(0.000)
Constant	3.7***	5.3***	6.2***	9.6***	6.32***	6.3***
	(1.01)	(1.41)	(0.97)	(2.55)	(0.210)	(0.254)
Observations	1,338	3,879	7,574	1,380	3,951	7,714
R^2 adj.	0.88	0.779	0.792	0.808	0.865	0.847

Notes: Standard errors are cluster at the neighborhood level in parentheses [a] p<0.01, [b] p<0.05, [c] p<0.1. Results are obtained from a Synthetic difference in differences using the PPML estimator. Columns (1) to (3) use 461m bandwidth at the periphery with social housing change dependant variable. Columns (4) to (6) use 461m bandwidth to the center with social housing change dependant variable. Columns (7) to (9) use 461m bandwidth at the periphery with private housing change dependant variable. Columns (10) to (12) use 461m bandwidth to the center with private housing change dependant variable. Column (13) shows the placebo effect of the Differences-in-Discontinuities estimate with pre-treatment data. Each estimate includes neighborhood and year fixed effects.

17 Online Appendix (not for publication): Placebo Test

Table (16) presents the placebo effect of the Differences-in-Discontinuities estimate with pre-treatment data. Instead of being treated in 2009, the treatment year is 2007, instead of being treated in 2011, the treatment year is 2008. The two treatments are not significant. Columns 14 and 15 show the results for treatments in 2007 and 2008 separately, and are not significant.

Table 16: Synthetic difference-in-differences with one treatment and placebo test for Differences-in-discontinuities

Dependent variable	Social Housing Change		
Bandwidth (in meter)	[0-461]		
	Differences-in-discontinuities		
	(13)	(14)	(15)
Treated in 2007	-0.0993	-0.0153	
	(0.0905)	(0.133)	
Treated in 2008	0.116		0.0500
	(0.118)		(0.137)
Nb of conversion	0.00452	0.00432	0.00448
	(0.00323)	(0.00324)	(0.00322)
Income (median)	-1.19e-05	-7.33e-07	-1.03e-05
	(0.000)	(0.000)	(0.000)
Constant	7.587***	7.377***	7.550***
	(0.744)	(0.621)	(0.701)
Observations	474	474	474
R^2 adj.	0.961	0.960	0.961

Notes: Standard errors are cluster at the neighborhood level in parentheses [a] p<0.01, [b] p<0.05, [c] p<0.1. Placebo effect of the Differences-in-Discontinuities estimate with pre-treatment data. Each estimate includes neighborhood and year fixed effects.