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 premises 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, and none of these policies have an impact on social diversity. We also show that these types of policies have adverse effects by increasing private housing prices.

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 objective 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,[4] hereafter called HLM (*Habitations à Loyer Modéré* which means moderate rent dwellings).[5] 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.[6]) into housing which provides incentive to invest in social housing. More precisely, three laws have been voted in 2009, 2011 and 2014 under the same principle that the surface of private housing redeveloped should be doubled for each conversion into commercial use (1:2 rule), but not for social housing (HLM) for which the compensated surface is identical (1:1 rule).

The aim of these laws were to increase the supply of housing in a satured spatial context where construction of new buildings were limited, as in many cities in the world. 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 different 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 construction of social housing in the center of Paris. In contrast, the 2011 law, and to a lesser extent

[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]Since the Solidarity and Urban Renewal Act ("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.

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

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

the 2014 law, were less resctrictive 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 $2x$ square meters of offices into private housing at the periphery of the compensation area. We show that this relaxation of the spatial constraint increased the change of use towards 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. Moreover, we find that these laws have triggered a rise in housing prices.

To analyse the spatial effect of these laws both at the border of the compensation area and in its center we use respectively a difference-in-discontinuity design and a synthethic difference-in-differences.

Our paper contributes to a large literature on the effects of local regulations on the supply of housing. Turner et al. (2014) provide a general analysis of the effect of land use regulation on price and welfare applied to the US. Gyourko and Molloy (2015) and Glaeser and Gyourko (2018) present how housing policies by restricting the supply (e.g. zoning) affects housing prices, wages and the form of the city. They however do not analyse convertion, and in particular not the potential spatial consequences of a compensation rule that plays on the supply of private housing *versus* the supply of social housing.

In the literature on 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). While we analyze a different relationship (conversion of private housing in commercial premises or social housing), we find a similar result, the policy on change of use enforced in 2014 has led to increase the price of private housing in Paris.

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 by using a synthetic difference-in-differences.

Finally the effect of public housing redevelopment on income seggregation has attracted a vast amount of work (e.g. Tach and Emory, 2017). Our contribution is in particular related to the work of Boustan et al. (2023) that analyze whether condominium development affects income and education levels. Their main conclusion is that, contrarywise to a common belief, a higher condo share due to local regulations do not have an effect on gentrification. In comparison, we study conversion into social housing. This enables to target more precisely how local government can, by this chanel, influence the social mix of a city. Like Boustan et al. (2023) we do not find a significant effect on social diversity.

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 other redevelopments, on price and 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 polit-

[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

ical, 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 premises.

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 district (arrondissement) where the change of use occurs. To gives 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) in that district 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 social housing, then the PRD "only" has to convert 300m² of commercial premises in private housing in that district.

This law concerns every change of uses that convert a private housing into commercial use. Then this policy covers various different situations and investors. For instance, beside the previous PRD example, a landlord that converts its housing into a short-term rental is also concerned by the law.

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).

An interesting aspect is that this policy, with its spatial constraint requiring conversion within the same district, can have vastly different effects depending on the scarcity of commercial premises available for compensation (see Online Appendix 7 for a simple model showing this). For instance in the city center, where the number of commercial premises available for conversion is scarce, the law can be highly restrictive (it may be just impossible to convert housing in office, because it is not possible to find the double of the surface of offices to compensate). As a result, this represents an incentive to invest in social housing. The situation may be different at the periphery of the compensation zone, where the opportunities to compensate are higher than in the center. In that case, the conversion of private housing in commercial use and the compensation leading to double the number of private housing is more likely. By defining the "Periphery" as neighborhoods located on the internal border of the compensation zone, and the "Core" as the center of the compensation zone, we can summurize this discussion as follows.

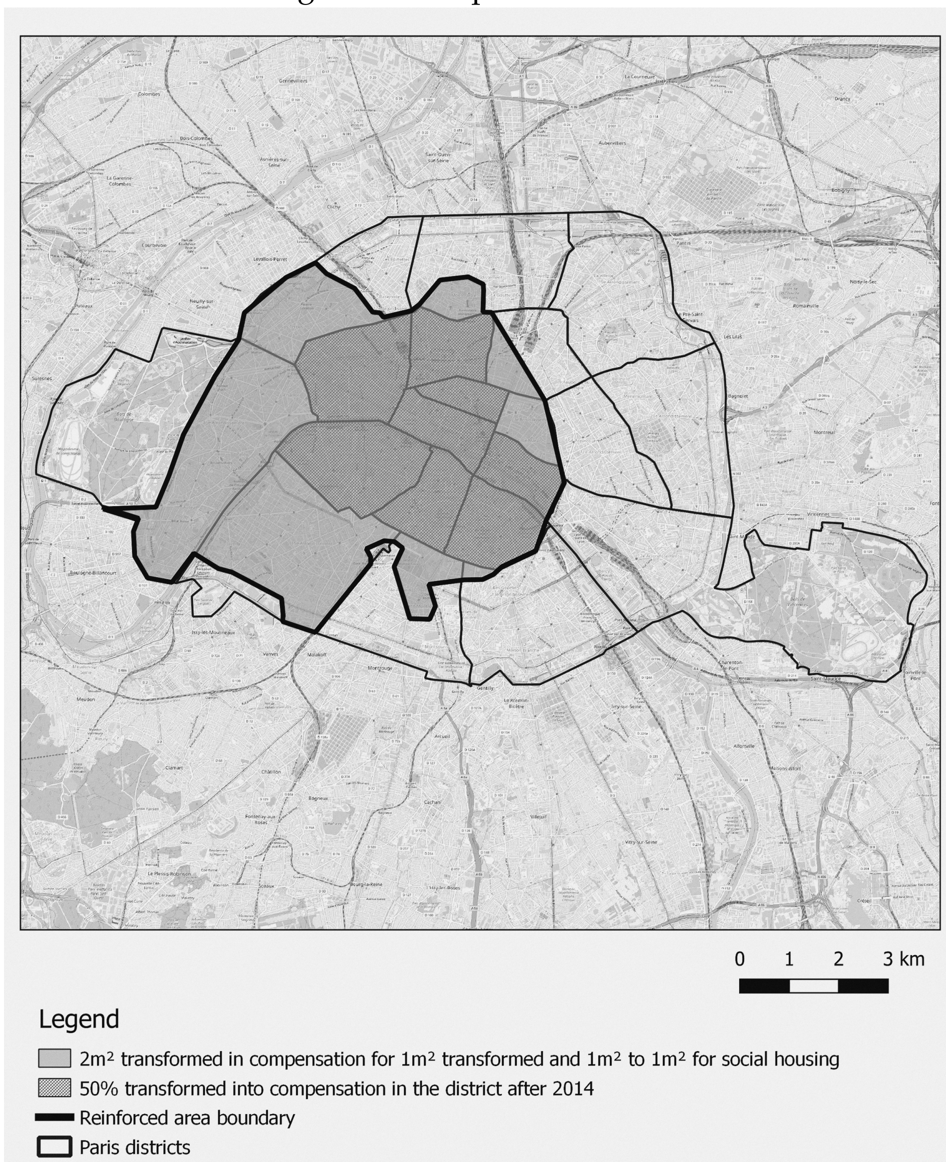
Proposition 1. *Testable Implications. A compensation law that stipulates compensation in the same district (law of 2009), under a relative higher scarcity of available redevelopment in Core than at the Periphery, implies:*

H1: In the Core: No significant effect on private housing (one for one), but significant increase in the number of social housing and significant decrease in the number of offices and/or commercial premises.

H2: At the Periphery: No significant effect on social housing but significant increase in the redevelopment of private housing (two for one) and significant decrease in the number of offices and/or commercial premises.

Map (1) 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 Core. For now it simply matters to notice that districts/neighborhoods, which are delimited by a gray line in Map (1), 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's also important to notice that the periphery of the compensation zone does not refer to the suburbs of Paris or 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, but to a lesser extent than in the center.

Figure 1: Compensation Zone



2.3 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 of use that is permanent. For him the compensation title looks like a tax or 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,[8] the average price is 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.

2.4 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 (i.e. not only in the district in which the change of use occurs). 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 rentals (e.g. Airbnb), can compensate by doubling the surface at the periphery. This simple change in the spatial opportunities to compensate can totally modify the different incentives. It becomes easier now to develop commercial premises in the center without compensation there which opens the door to a reduction of private housing in the center. This law also relax the incentive to convert housing into HLM in the center. At the periphery, we have now an increase in the competition to convert housing (due to the demand of conversion from investors in the center), this may generate a crowding effect. PRD that usually converts housing in offices at the periphery (e.g. before 2011), finds now that the 2:1 rule is more binding there, and then can decide to invest in social housing.

In summary, this law can have the following implications.

Proposition 2. *Testable Implications. A compensation law that enables the Core to compensate at the Periphery (law of 2011) implies, under the assumption of a relative higher scarcity*

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

of available redevelopment in Core than at the Periphery, that:

H1: In the Core: No significant effect on social housing, reduction of private housing and a significant increase in the number of offices and/or commercial premises.

H2: At the Periphery: Significant increase in the redevelopment of private housing (two at the periphery for one lost in the center), significant increase in social housing and significant decrease in the number of offices and/or commercial premises (crowding effect).

However, with the development of short-term rentals in the center of Paris, the market background has progressively changed with the risk to observe a decrease in the number of private housing due to this wide spatial compensation rule. Hence 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.

2.5 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.[9] 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.

[9] 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 use

Our dependent variables are successively change of use toward HLM (Section 3 and 4) and toward private housing (Section 5). These data come from the Land Registry Files provided by CEREMA (Center for Studies and Expertise on Risks, Environment, Mobility, and Spatial Planning).[10] This dataset enables the identification of housing units that have undergone a change of use, 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 use 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). 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 use.

About zeroes (no change in use)

Neighborhoods where there are no housing units that have undergone changes in use 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

[10]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.

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 use (and which are, in fact, implicitly targetted by the different laws).

2.6.2 Explanatory variables

Income

Income by impacting on the demand of housing, and then housing price, indirectly affects the demand of conversion of private housing in commercial use and/or social housing. 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

The median income may be a poor proxy of the market dynamics that explains the demand of private housing in some districts. In particular, the gentrification process that progressively makes a location trendy cannot be captured by the median income. To take this demand effect into account, we use data on Airbnb. Short-term rental can be a direct determinant of social housing due to these laws, since any change of private housing into that use is subject to the compensation. Furthermore, an indirect effect is also possible since short-term rentals cause a displacement of the poorest (Belloy, 2023) and fosters gentrification (Wachsmuth and Weisler, 2018) which can play against the effects of the laws we study here. As argued by Wachsmuth and Weisler (2018), Airbnb does not overlap completely with the different stages of gentrification, there is in particular poor neighbourhoods that experiences gentrification pressures but which are not yet considered as desirable destinations for tourists. But if we put aside this earlier stage, short-term rentals are often located in the 2nd- or 3rd-wave of the gentrification process and are often considered as a demand determinant on the housing market (Hackworth and Smith, 2001).

Airbnb data comes from the Open Data Soft platform, a French company that makes these data available. More precisely the 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). These 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.

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[11] and then represent an available source for individuals.

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.

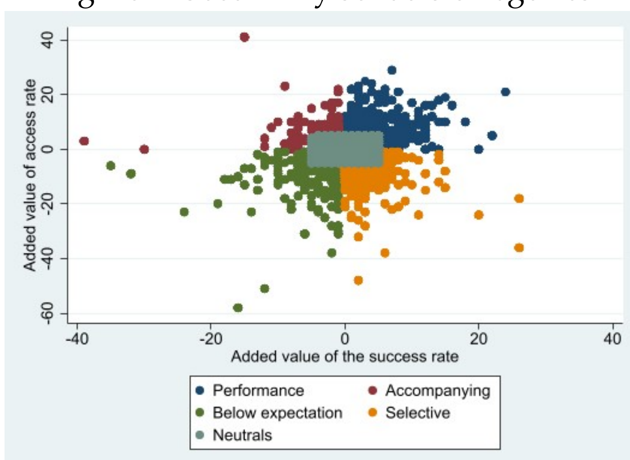
Schools can then be classified as "neutral", "performance", "accompanying", "below expectation" and "selective". Figure 2 represents these different categories along the success rate on the horizontal axis and the access rate on the vertical axis.

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

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.[12]

Figure 2: Secondary schools categories



[12]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.

3 Effects of conversion laws at the dividing line

3.1 Empirical strategy

3.1.1 Spatial Regression Discontinuity Design in Differences

The spatially delimitation of the compensation area suggests an identification strategy based on a Spatial Regression Discontinuity design (SRD) in order to study the effect of these laws at the Periphery of the compensation zone (Keele and Titiunik, 2015). Indeed the housing market and even the carasteristics of neighborhoods are very 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).[13]

We then estimate the following equation:

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

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

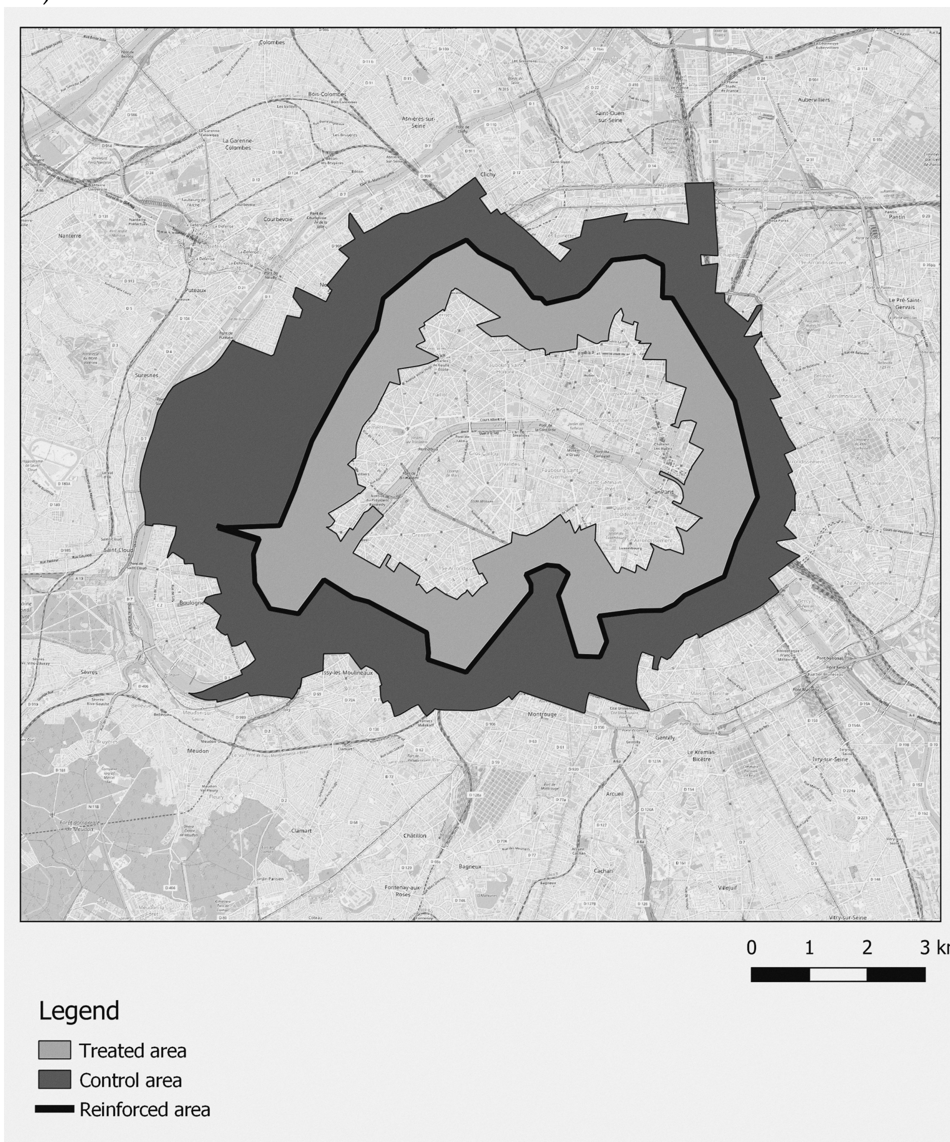
where $Y_{it}^{\flat}$ is the number of square meters of social housing newly created (i.e. resulting from a change of use) in the neighborhood i at the time t. As explained in the data section, this variable includes neighborhoods with no transformation and then lead us to use the Pseudo Poisson Maximum Likelihood estimator.[14]

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 gray, the control group is in dark gray.

[14]Similar results are obtained with OLS (without zeroes) in the Online Appendix (11).

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 social housing created (belonging to the spatial window $\flat$) 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, but the main advantage is that it enables to control for the different laws. 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. However, to assess the magnitude of this bias, we estimate again Equation (1) by analyzing separately the three different laws in the Online Appendix (13), we find similar results.

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 (9) 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 approach as described in what follows.

3.1.2 Synthetic Difference-in-Differences

The Synthetic Difference-in-Differences estimator of Arkhangelsky et al. (2021), hereafter SDID, has the advantage to reweights and matches pre-exposure trends. 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 our previous approach. The similarity of the control group is indeed always debatable in spatial Diff-in-Disc, and maybe even more for Parisian neighborhoods, in this context the SDID provides a good alternative.

The goal of this method is to weight the control units and treated units in the pretreatment period to make these different units comparable 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:

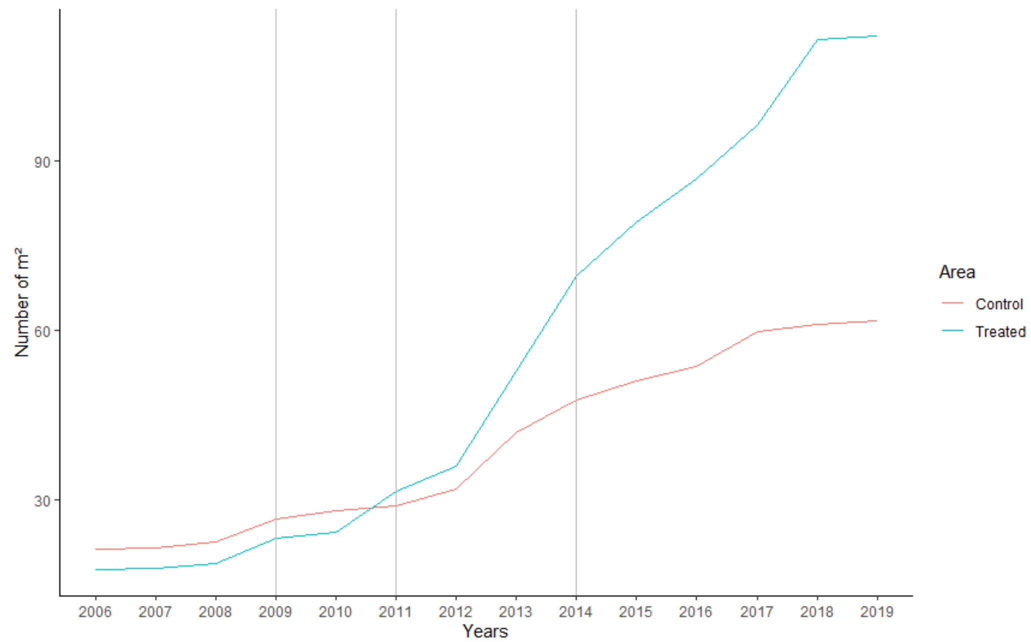
$$\hat{\tau} = arg\, min \left\{ \sum_{i}^{N} \sum_{i}^{T} (Y_{it} - \epsilon_{it} - \eta_i - \Gamma_t - Z_{it})^2 \hat{\omega}_i^{sdid} \hat{\Delta}_t^{sdid} \right\},$$

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 (8).[15]

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

Figure (4) illustrates change in the convertion of HLM (in m²) 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 4: Treated and Control Areas in the Synthetic difference-in-differences at the border (bandwidth: 600 meters)



It is worth noting that the inclusion of these three treatments in the same estimation can only be achieved by constructing a synthetic group based on a single pre-treatment period, specifically the one before the first treatment (i.e. 2009). Another approach is tested in the Online Appendix (13), where we construct a synthetic control prior to each treatment and analyze the impact of the different laws separately. The graphics obviously differ but similar results about the effects of these laws are obtained.

We conducted a series of estimations by considering the same set of treated districts than in the previous section, namely with distance from the border of the rein-

[15]We also present results with the nonparametric synthetic control method developed by Cerulli (2020) in Online Appendix (12).

forced area using the bandwidth presented previously. The aim is to provide results that are directly comparable with those presented until now. We refer to this empirical strategy as the "periphery" estimation.

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 bright grey area of the previous Map 3, while the untreated are selected in the dark gray area of the Map 5 below.

3.2 Results

3.2.1 Difference-in-Discontinuities

Table (1) presents the results of the spatial difference-in-discontinuity with different bandwidth choices (see Appendix 9 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 Proposition 1, the spatial definition of this legislation, which stipulates that changes of use must occur within the same district, may not be particularly restrictive at the periphery of the compensation zone which can explain this null-result.

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 of 90.2% 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 Core to the Periphery may have led to a crowding effect, reducing the availability of offices that can be converted. This, in turn, could have prompted PDR to invest in social housing, which requires less office/commercial space for compensation.

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 crowding effect at the Periphery) but less so than the 2009 one. [16]

[16] See Online Appendix (14) 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	0.686*	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 premices converted thay 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 as expected, 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 controling 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 that are a proxy for the increasing attractiveness of some districts and indicator of schools added value that may influence the residential choice and then the housing market (see the data section for motivations).

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. Surprisingly, Airbnb is positive when introduced alone or with all other controls, but it loses its significance once fixed effects are introduced. The indicators of the added value of schools have the expected signs; for instance, high performance, which may stimulate residential demand from households, has a negative effect on HLM conversion. However, almost all these variables 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 neighborhood characteristics 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.

3.2.2 Synthetic difference-in-differences

We reproduce here the same analysis but we change the control group, which is now a synthetic area of the treated one (as discussed in the empirical strategy section). This analysis is thus a robustness check of the previous one.

Table 4 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 in the previous section, with the 2009 law demonstrating no significant effect, while the 2011 and 2014 reforms successfully promoted the construction of social housing. [17]

Table 4: 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 m²). Each estimate includes neighborhood and year fixed effects

The inclusion of additional controls in the last Column of Table (4) and in Table (5) 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

[17] See Online Appendix (13, Column 1-3) for estimates with one single treatment

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. What about elsewhere?

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

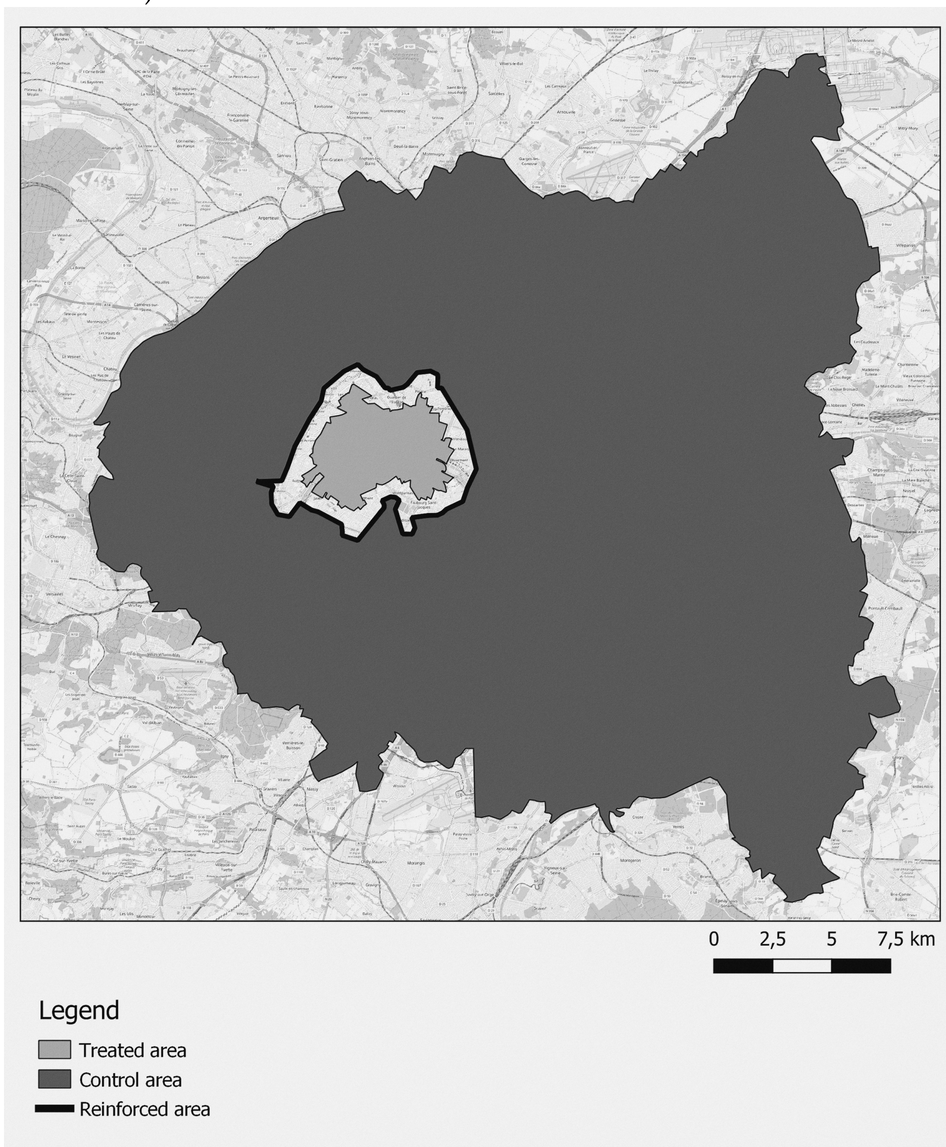
Bandwidth choice	CE-opt [-461,461]				
	Conversion	Income	School AV	Airbnb	FE
Treated in 2014	0.370*	0.377**	0.401**	0.366**	0.335*
	(0.204)	(0.183)	(0.192)	(0.185)	(0.179)
Nb of conversion	0.0429***				0.0120***
	(0.0077)				(0.0045)
Income (median)		-0.0024**			-0.0045***
		(0.0009)			(0.0045)
Airbnb				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.

4 The effects of conversion laws in the heart of Paris

A second series of estimations is carried out using a complementary approach in order to analyze the impact of the law in treated districts at the center of Paris. 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 bright gray, the synthetic control is built on districts located in the dark gray area.

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



We refer to this empirical strategy as the "Core" estimation. The aim of this strategy is to analyze the spatial effect of each policy differently. 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. Hence, the previous Diff-in-Disc estimation, as well as the border estimation, are simply unable to capture such an effect. In contrast, the current spatial delimitation is designed to understand how this policy has fostered social housing change in this interior 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 increase in the synthetic region seems to decelerate in comparison to the area where the 2014's law has been implemented. In the Online Appendix (13), 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 6 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 for changes in the center 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 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 (9) also shows that once we go beyond the 600 meter threshold, the coefficient starts to lose its significance. This tend to illustrate that the impact of the 2009 law in the center is however not totally fullfilled. To verify this, we estimate again this Synthetic Difference in Differences equation on an high-demand zone in the center of Paris (Arrondissement 1, 7 and 8). We find no significant effect (Column 6).[18]

[18] See Online Appendix (13, Column 4-6) for estimates with one single treatment.

Table 6: Social Housing Change from Synthetic Difference in Differences

Treated:	Core						
Bandwidth choice	ad-hoc		MSE-opt	CE-opt		High-dem	High-dem with control
Bandwidth (in meter)	]300-center]	]600-center]	[1314-center]	[461-center]		Arrond 1, 7, 8	Arrond 1, 7, 8
Treated in 2009	0.620**	1.236**	4.783	0.929**	0.830*	2.231	2.183
	(0.291)	(0.620)	(3.320)	(0.469)	(0.429)	(2.301)	(2.452)
Treated in 2011	0.0567	-0.433	0.909	-0.411	-0.340	0.349	0.366
	(0.255)	(0.406)	(2.742)	(0.299)	(0.281)	(0.527)	(0.443)
Treated in 2014	-0.184	-0.607	6.506	-0.470	-0.458	-0.393	-0.445
	(0.425)	(0.720)	(4.764)	(0.598)	(0.601)	(0.420)	(0.463)
Nb of conversion					0.0081***		0.0039***
					(0.0012)		(0.0009)
Income (median)					-0.0006		0.0013
					(0.0006)		(0.0016)
Constant	5.547***	5.719***	5.096***	5.641***	5.871***	4.615***	4.177***
	(0.242)	(0.279)	(0.453)	(0.262)	(0.267)	(0.551)	(1.029)
Observations	7,910	7,574	6,930	7,714	7,714	6,972	6,972
R^2 adj.	0.833	0.847	0.865	0.836	0.843	0.849	0.853

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 m²). Each estimate includes neighborhood and year fixed effects

We pursue this analysis in Table (7) 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 7: 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, price and social diversity

Until now we have only analyzed the impact of the compensation laws on social housing. But a second objective of these laws were also to foster private housing. The 2 for 1 rule for instance implies that any redevelopment toward commercial premises should lead to double the surface of private housing. However such an increase in the redevelopment of private housing is more likely to occur at the Periphery under the 2009 law (Proposition 1). In contrast the 2011, could have led to a decrease in the number of private housing in the Core compensated by an increase at the Periphery

(Proposition 2). Thus the first aim of this section is to test these predictions. But we also go beyond this research, by analysis the impact of these laws on housing price. In particular the decrease in the number of private housing in the Core after the 2011 law (and to a lesser extent after the 2014 one) should lead to an increase in the housing price (Proposition 2). Finally since the aim of these laws were to foster more social diversity in the capital, we end up by analysis this topic.

5.1 More private housing in Paris?

We replicate here the earlier analyses with the SDID method[19] with a simple change of the dependent variable; we now take into account the redevelopment of private housing due to the compensation rule.

Table (8) reports the results. Contrary to what Propositions 1 and 2 suggest, we do not observe any difference between the Periphery and the Core here. However, as anticipated by the regulator, these compensation laws have indeed stimulated the redevelopment of private housing throughout the entire compensation zone. This observation even holds true in high-demand zones.

For the 2014 reform the conclusion is more difficult to reach. This regulation seems to have no effect in Column 1, 3 and 5 where only total convertion are used as control in our sample over the whole period (2006-2019). The sign of the coefficient is however negative, and once we restrict the sample for the time analysis that enables to take into accound data on Airbnb (2012-2017), a significant reduction in private development is observed.[20]

[19]We do not find convincing pre-trend for the diff-in-disc, see the Online Appendix (10), which leads us to give up these estimations for private housing redevelopment.

[20]See Online Appendix (13, Column 7-12) for estimates with one single treatment.

Table 8: Private redevelopments

Method	Periphery		Core		High-dem zone	
Bandwidth (in meter)	[0-300]		]300-center]		Arrond 1, 7, 8	
Treated in 2009	0.306***		0.258***		0.529**	
	(0.110)		(0.093)		(0.234)	
Treated in 2011	0.196***		0.226***		0.646***	
	(0.073)		(0.063)		(0.086)	
Treated in 2014	-0.014	-0.111***	-0.040	-0.157***	-0.032	0.0551
	(0.046)	(0.037)	(0.038)	(0.046)	(0.054)	(0.0801)
Nb of conversion	0.006***	0.005***	0.004***	0.003***	0.004***	0.0040***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0006)
Income (median)	0.0005	0.0002	-0.0002*	0.0001	-0.0002*	-0.0002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Airbnb		0.003***		-0.001		0.0030
		(0.001)		(0.001)		(0.0019)
Constant	6.79***	7.65***	7.38***	7.79***	7.39***	7.964***
	(0.255)	(0.216)	(0.10)	(0.058)	(0.121)	(0.0630)
School added value		✓		✓		✓
Neighborhood FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28798	3570	31500	4134	28434	2436
R^2 adj.	0.94	0.97	0.94	0.97	0.95	0.95

Notes: Standard errors are cluster at the neighborhood level in parenthesess ^{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) and (2) use 300m bandwidth at the periphery. Columns (3) and (4) use 300m bandwidth to the center inner compensation zone. Columns (5) and (6) represent high demand neighborhoods. The dependent variable is the number/area of private housing conversions (in m²).

5.2 An even more expensice city

To analyse housing price, we use the real estate price data that comes from the Demande de Valeurs Foncières (DVF) files, also provided by CEREMA and sourced from the DGFiP, which compile all real estate transactions from 2010 to 2019. This time period implies that the effect of the law implemented in 2009 cannot be studied, and even the study of the 2011 regulation is critical (only one year before), then we use these data only to study the 2014 compensation law.

Using the raw data, we observe an increasing in housing price over the period. In Paris, outside the compensation zone, the selling price per m² was €5,354 in 2012 compared to €6,203 in 2019. In the compensation zone, the selling price per m² went from €8,755 to €11,213 in 2019. The research question is thus to determine whether the 2014 law has contribuated to this increase. Table (9) present the result of our causal analysis based on the SDID method. We find that these new regulations have indeed participated to increase price in the capital.

As explain in the background section, the 2014 law is a mix of the two previous laws and hence its effect are relatively undeterminated (Proposition 1 and 2 cannot be used due to the rule implying that at least 50% of the compensation should be done in the Core). Furthermore this law is the last one and then cumulative effects are likely.

A plausible interpretation that reconciles this increase in price with the previous results is that at the onset of the period, in 2009 and 2011, opportunities for conversion were sufficiently high; consequently, the increase in price stimulated the supply of other types of redevelopment in particular commercial premises that require to double the surface of private housing. However, by 2014, the "2:1 rule" had become extremely binding, drastically limiting opportunities for compensation. As a result, even with rising prices, redevelopments for uses other than social housing became virtually impossible. While it might be tempting to conclude that the law achieved its objective in this case, this is only partially true. New social housings were indeed converted, but only in peripheral areas (see Table 1, 2) where the law had significant impact, not in central areas (see Table 4) where the law proved insignificant.

Table 9: Housing price

Type	Periphery		Core	
Bandwidth (in meter)	[0-300]	[0-600]	[300-center]	[600-center]
Treated in 2014	0.0833*	0.0925**	0.107***	0.104***
	(0.048)	(0.043)	(0.035)	(0.037)
Garage/parking type	-0.0022***	-0.0022	-0.0056*	-0.00433
	(0.001)	(0.002)	(0.003)	(0.003)
Number of houses	0.0416	-0.0325	-0.234**	-0.214*
	(0.041)	(0.080)	(0.109)	(0.119)
Cellar / attic / storeroom	0.0092	0.0031	-0.022**	-0.0236**
	(0.011)	(0.009)	(0.010)	(0.012)
No more than one room	0.0021***	0.0034**	0.0069**	0.005**
	(0.000)	(0.0012)	(0.003)	(0.003)
At least 5 main rooms	0.0111	0.0133	0.0469*	0.0497*
	(0.030)	(0.027)	(0.025)	(0.026)
Constant	8.807***	8.906***	9.035***	9.047***
	(0.045)	(0.043)	(0.034)	(0.033)
Observations	4,624	5,039	5,512	5,097
R^2 adj.	0.435	0.394	0.452	0.490

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. Column (1) use 300m bandwidth at the periphery. Column (2) use 600m bandwidth at the periphery. Column (3) use 300m bandwidth to the center inner compensation zone. Column (4) use 600m bandwidth to the center inner compensation zone. We also introduce as control the number of units with 2, 3, 4 main rooms, and the umber of "terrace" type additional rooms, but these variables were not significant and hence not reported here. The dependent variable is the median housing price by neighborhood. Each estimate includes neighborhood and year fixed effects

5.3 Impact on social diversity

The ultimate aim of these laws was to foster diversity among the socio-professional categories of residents in the city of Paris. Did it succeed?

Socio-economic indicators

The data on the distribution of socio-professional categories is derived from the INSEE census (National Institute of Statistics and Economic Studies, Classification of Professions and Socio-Professional Categories[21]) 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 higher intellectual

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

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 closer the index is to 1, the more heterogeneous the neighborhood is, i.e., the more homogeneous the Socio-Professional Categories are represented.

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, the higher intellectual professions.[22] 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

[22] 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).

Results

In Table (10) we present the effects of these housing regulations on the location choice of the different social-economic categories.

Table 10: 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).[23] 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.[24]

In Table (11), 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.

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

[24] 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 11: Location quotien- Core

Type	Managers				Workers				Theil Index	
	Location quotien		Share		Location quotien		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.

Obviously the distinction done here, between higher intellectual professions and workers is an oversimplification that doesn't fully capture the complexities and nuances of occupations. This binary classification ignores the wide range of parisian jobs, for example, workers in the creative industries, (fashion, graphic design, digital marketing, etc.) do not fit easily into either category. Finally the spatial distribution of these two occupations may not adequately capture the multi-faceted nature of gentrification and the various socioeconomic groups involved. In a similar way, the Theil index which takes into account all categories, is certainly not enough accurate to analyze the detail of social diversity. These results however provide a general idea, if change occurs it is not at that general level.

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 12) which is not significant in other estimation (Column 2, 3, 4).

Table 12: 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[25] and several local policies have been implemented. In this study, we examine three successive laws implemented in 2009, 2011, and 2014 to promote the conversion of offices and other commercial premises into social housing. A certain amount of trial and error can be observed in the pol-

[25]In San Francisco, for instance, several demonstrations have been organized 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.

icy 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 a tool to fulfill the commitment to build 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 evaluation, 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, but not in the most privileged areas. The 2011 and 2014 laws present a reversed picture, 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.

Finally, our analysis of these laws' effects on private redevelopment uncovers some unexpected findings. The early legislation (2009 and 2011) appears to have encouraged private housing redevelopment, possibly due to an increased housing price that spurred the conversion supply. Conversely, the most recent law (2014) set off an eviction effect at the outskirts (more social housing, less private housing), while only hampering private housing in the city center (with no additional social housing). This marks again a partial failure of this regulation in its attempts to tackle income segregation, particularly in areas where it is most severe. We reinforce this interpretation by finding a lack of impact from these redevelopments on social diversity indicators.

Although our analysis presents a relatively strong internal validity, it obviously lacks the external one. While we can defend that the redevelopment policies aimed at social housing have no significant impact on spatial income diversity in Paris, we cannot generalize this conclusion to other locations and different time frames. More research needs to be conducted in various cities and across different periods to gain a deeper understanding of how redevelopment influences the spatial and social fabric of cities.

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7 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 effects 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 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[26] 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.[27] 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 an household or to a social landlord at:[28]

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

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

[26] 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.

[27] 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.

[28] 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".

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.[29]

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 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:

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

[29] 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.

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.[30] 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).[31]

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[32] 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.

[30]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.

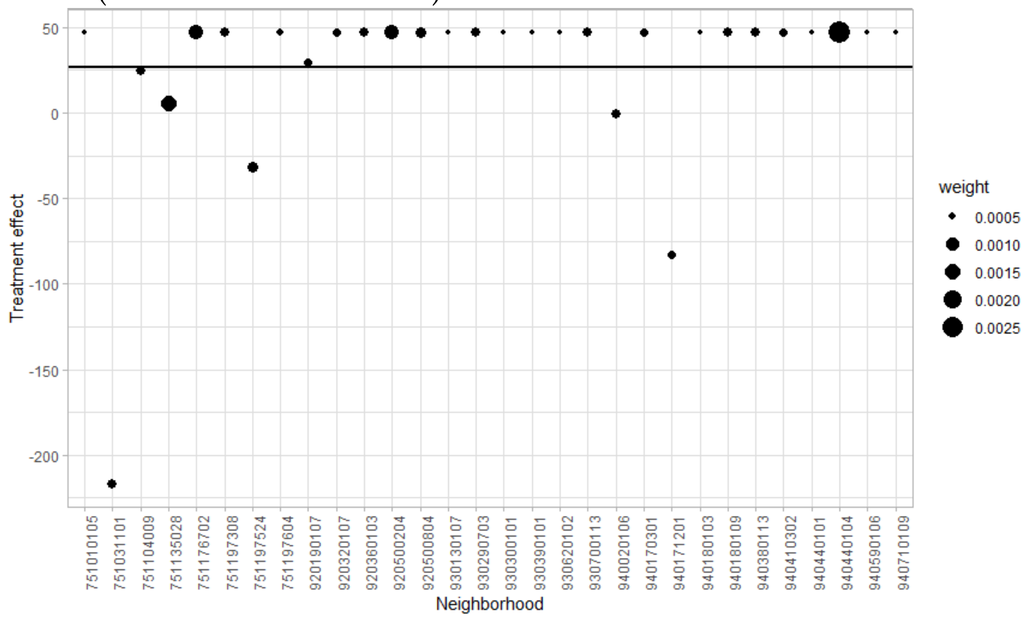
[31]In that case the mechanism may play as follows, an increase in the number of firms in one location, directly reduce the supply of converted unit and increase the price of land, but also indirectly increase the potential number of resident for a given supply of floor space. This, in turn, bids up 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.

[32]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.

8 Online Appendix (not for publication): size of weights

The weights used to build the synthetic controls are presented in Figure 7 and present relatively few extreme values.

Figure 7: Weights of the top 30 neighborhoods in the Synthetic Difference-in-Differences (bandwidth: 600 meters)



9 Online Appendix (not for publication): plethora of bandwiths but still the same results

Table (13) provides the main results of the Diff-in-Disc for the different bandwidths. Table (14) the estimation at the periphery with the SDID and (15) at the center.

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Table 13: 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 14: 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 15: Difference in Differences of Social Housing Change - Core Estimation

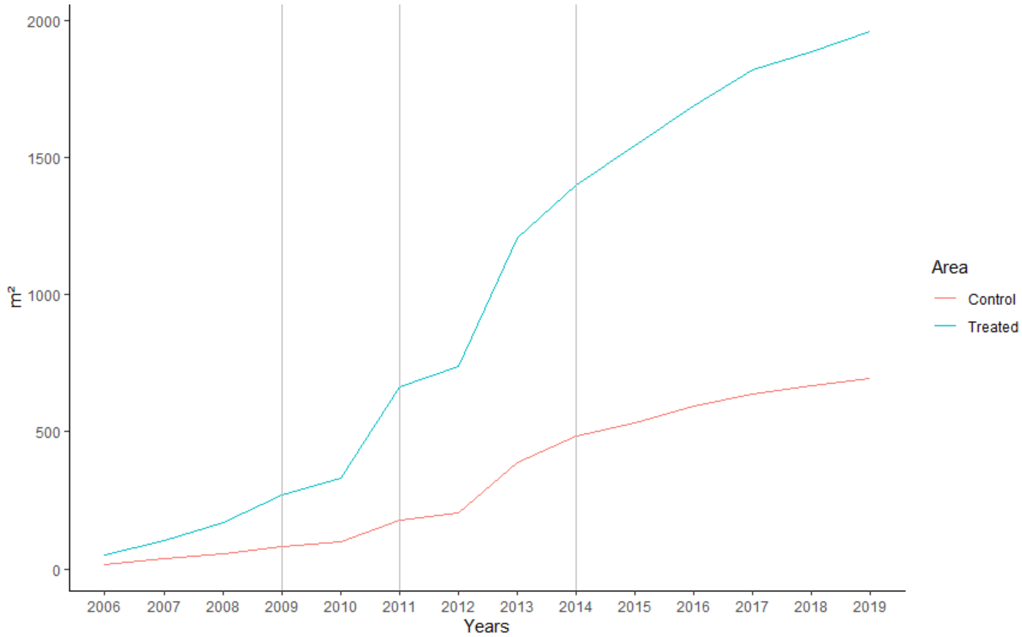
Bandwidth	300	400	500	600	700	800	900
Treated in 2009	0.620**	0.737**	1.065**	1.236**	1.376	2.794**	3.109
	(0.291)	(0.364)	(0.486)	(0.620)	(0.898)	(1.388)	(2.420)
Treated in 2011	0.0567	-0.128	-0.426	-0.433	-0.931*	-1.551***	-0.620
	(0.255)	(0.284)	(0.318)	(0.406)	(0.529)	(0.583)	(0.855)
Treated in 2014	-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 $p<0.1$

10 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 8.

Figure 8: Treated and Control Areas in the Difference-in discontinuities for private housing change (bandwidth: 600 meters)



11 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 (16), 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 16: 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.

12 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 9 indicates an optimum bandwidth of 1 which is then the optimal vector distance (Mahalanobis distance) between treated units and controls within the bandwidth. Figure 10 shows the results of the counterfactuals 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 9: Optimal bandwidth for the non-parametric synthetic control method

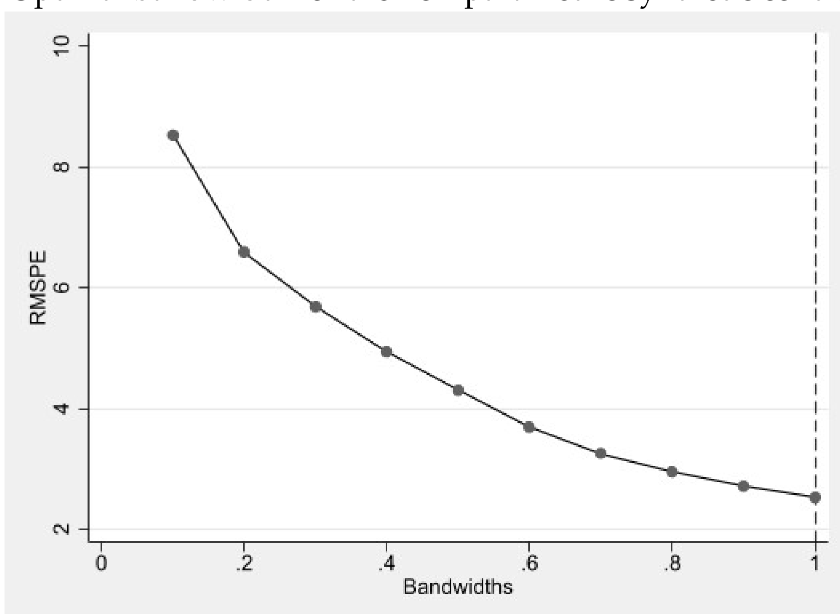


Figure 10: Non-parametric synthetic control method

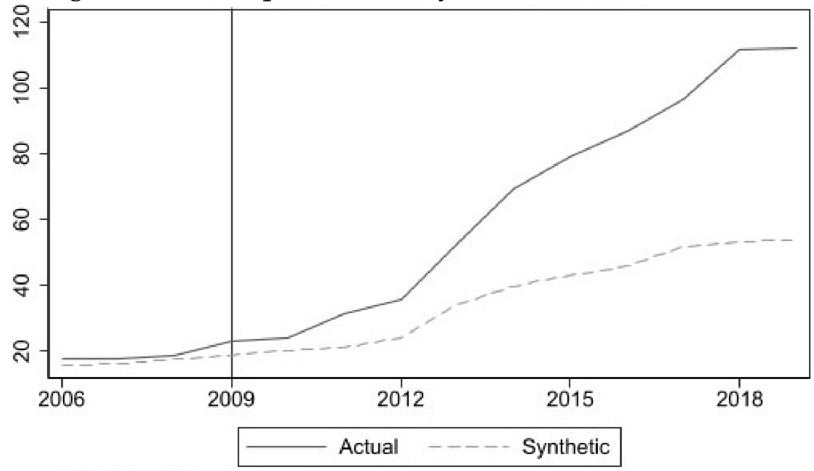


Figure 11: Synthetic control method

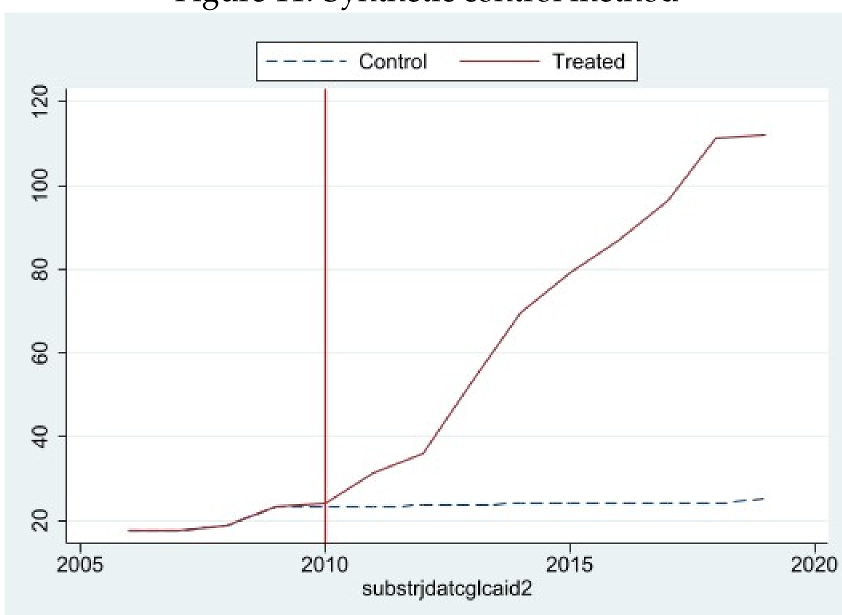
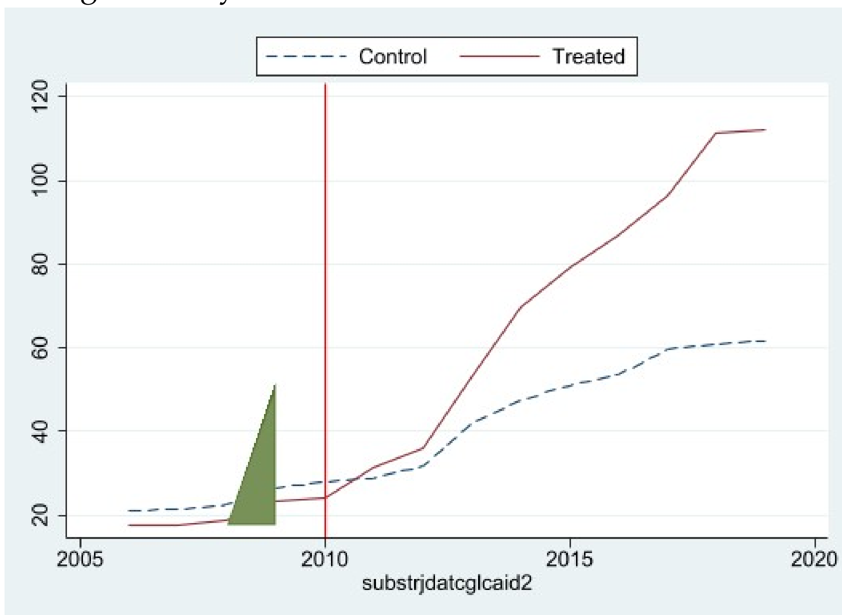


Figure 12: Synthetic difference-in-differences method



13 Online Appendix (not for publication): One single treatment by estimation

Table (17) 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 17: Synthetic difference-in-differences with one treatment and placebo test for Differences-in-discontinuities

Dependent variable	Social Housing Change						Private Housing Change					
Bandwidth (in meter)	[0-461]			]461-center]			[0-461]			]461-center]		
	Synthetic difference-in-differences											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated in 2009	0.043			0.665*			0.310***			0.172*		
	(0.14)			(0.439)			(0.096)			(0.099)		
Treated in 2011		0.423			-0.099			0.275***			0.187*	
		(0.302)			(0.372)			(0.0912)			(0.099)	
Treated in 2014			0.481*			-0.395			0.041			-0.396***
			(0.304)			(0.628)			(0.052)			(0.063)
Nb of conversion	0.01***	0.03***	0.005***	0.02***	0.019***	0.008***	0.012***	0.007***	0.004***	0.010**	0.007***	0.004***
	(0.003)	(0.004)	(0.002)	(0.006)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)
Income (median)	0.006	-0.001	-0.002	-0.014	-0.0013*	-0.000	-0.003	-0.0007	0.0003	0.000	-0.001	-0.001*
	(0.000)	(0.005)	(0.003)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	3.7***	5.3***	6.2***	9.6***	6.32***	6.3***	7.3***	7.2***	7.4***	6.3***	7.1***	7.2***
	(1.01)	(1.41)	(0.97)	(2.55)	(0.210)	(0.254)	(0.752)	(0.332)	(0.254)	(0.374)	(0.084)	(0.0512)
Observations	1,338	3,879	7,574	1,380	3,951	7,714	8,916	14,373	16,296	9,444	13,293	30,814
R^2 adj.	0.88	0.779	0.792	0.808	0.865	0.847	0.888	0.914	0.947	0.878	0.913	0.938

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.

14 Online Appendix H (not for publication): Placebo test

Table (18) 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 and finally the third treatment is 2009. The first two treatments are not significant, while the 2009 treatment year, which is the first year of the law enforcement, is significant.

Table 18: 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)
Treated in 2007	-0.142
	(0.102)
Treated in 2008	0.159
	(0.122)
Treated in 2009	0.953**
	(0.418)
Nb of conversion	0.00958***
	(0.00282)
Income (median)	-0.00371
	(0.00291)
Constant	7.581***
	(0.724)
Observations	2,002
R^2 adj.	0.898

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.