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 on housing prices, by reducing the supply for private housing, they lead to an increase in its price.

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

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this social phenomenom, leading the movement of YIMBY (*Yes In My Back Yard*) to support more private and public housing (Dougherty, 2020).

In this study, we investigate a range of urban regulations in Paris, where the YIMBY label is not employed, but the shared objective of promoting social diversity and ensuring affordable housing is clearly evident. In particular the city of Paris has indirectly subsidized the conversion of offices into affordable housing units in districts where wealth is concentrated. Paris has indeed a long history to concentrate a disporportionate high level of rich in its center in comparison to its metropolitan area and to the rest of France.[1] To combat this long-term trend, several laws have been voted in the past decades, including rent control[2] and a steady increase in the minimum quota of social housing,[3] hereafter called HLM (*Habitations à Loyer Modéré* which means moderate rent dwellings).[4] Beside these standard policies, the city of Paris has passed in 2009 a new act regarding the conversion of shops and offices (but also warehouses, restaurants, hotels, cinema, etc.[5]) into housing which provides incentive to invest in HLM. More precisely, three laws have been voted in 2009, 2011 and 2014 under the same principle that the surface should be doubled for each conversion into housing (1:2 rule), but not for social housing (HLM) for which the compensated surface is identical (1:1 rule).[6]

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 dif-

[1] 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.

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

[3] 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.

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

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

[6] The law has evolved as to where compensation must be done. The 2009 regulation required compensation in the same district, but the Paris Council in 2011 enlarged that area, and finally the 2014 regulation required that in eight districts, at least 50% of the area should be compensated in there.

ferent spatial effect making them more or less efficient to impulse more social diversity. For instance, the 2009 regulation, which was the most restrictive since it imposed compensation within each district, succeed to foster the construction of social housing in the center of Paris, though not in high-demand areas. In contrast, the 2014 law, and to a lesser extent the 2011 law, only increased the surface area change of use towards social housing at the outskirts but not in the center, where the concentration of the richest population is most deeply rooted. Confirming this result, we find that these laws have had no significant effect on social diversity measured by occupation. We have also found that these laws, by reducing the supply of private housing, have led to an increase in prices.

To analyse the spatial effect of these laws both at the border of the compensation area and in its center (which is also the center of Paris) 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 from this relaxation, 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 do not analyze this price premium, we however find that the policy on change of use implemented in 2014 has had a positive impact on the price of 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 (which equates to over half of a pre-regulation standard deviation and 27 thousand nights spent per month). 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 gentrification 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 gentrification.

Section 2 presents the different laws and the historical urban background in Paris. We also present 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 cost to compensation tend to be higher in areas with high tension. For that reason, 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. The last Section concludes.

2 Background

2.1 Conversion into housing

Paris has a long history to concentrate a disporportionate high level of rich in its center in comparison to its metropolitan area and to the rest of France.[7] 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,[8] linked to its persisting centralization of the french political, financial and mediatic organizations have magnified this residencial seggregation between the city center (*alias intra-muros*) and its periphery. The gentrification from the West of Paris (an historical central place for the upper class), has spread to the entire historic center of the city. By contrast, from the 1960s onwards, the suburbs disproportionately attracted the low- and middle-income classes (Clerval, 2010).

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

In 2009, a compensation zone is created, in which the surface should be doubled in the same district (arrondissement) where the change of use occurs. However, to increase the stock of social rental housing, the rule of doubling the surface does not apply for HLM.

The compensation can be carried out directly by the applicant, who offers as

[7] 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.

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

compensation premises that he owns, 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.

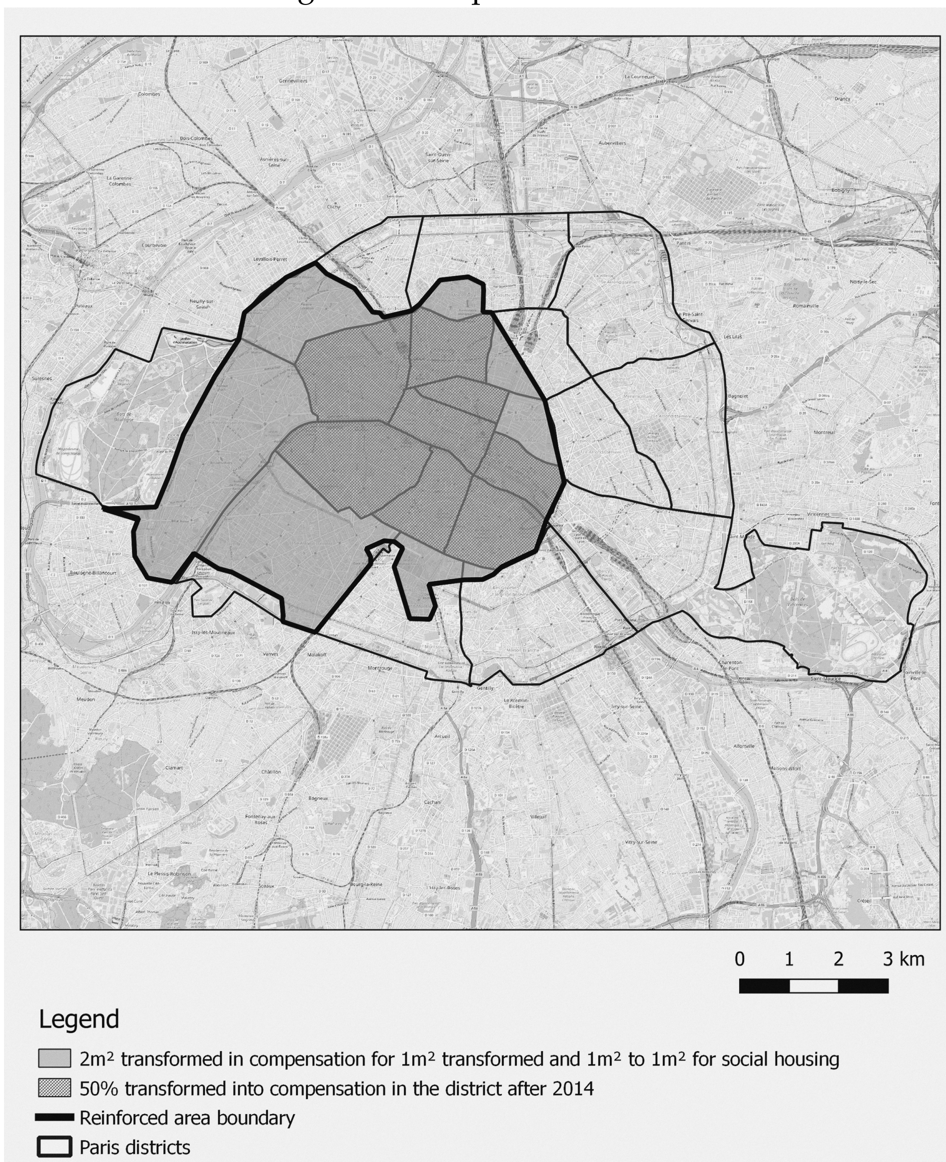
This transfer of commerciality from a property for use other than housing to a residential property, allowing the applicant to obtain a change of use that is real, that is to say, permanent. For him the compensation title looks like a tax or an administrative cost to convert its building.

It is important to notice that there is no official price for these titles (and we have no data for it), 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,[9] 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.

In Map (1) the compensation zone is delineated by a black line. Inside this zone, there is a compensation of 2m² for a transformation of 1m² in case of residential housing, and, a compensation of 1m² for a transformation into social housing. District are delimited by a gray line inside this compensation zone. The 2009 regulation has been the most restrictive, because the compensation (2 for 1, or 1 for 1) should be done in the same district where the premise is transformed.

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

Figure 1: Compensation Zone



In 2011, the law is amended to be less restrictive. All the enhanced compensation zone is concerned by the possibility to compensate (and not only in the district in which the change of use occurs). To give an example an office converted in private housing in the center can be compensate by doubling the surface at the periphery.

However, with the development of short-term rentals in the center of Paris, and the "professionalization" of these rentals, the market background has progressively changed in Paris. 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 done there (the eight districts are represented in dark gray in Map 1).

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.[10] 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.

2.2 Partial Equilibrium

Based on Garcia-López et al. (2020), the objective of this section is to present a simple yet formal framework to discuss not solely the mechanism by which regulation affects the supply of conversion, but also to pinpoint demand shifters that should be controlled 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 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

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

to compensate elsewhere.[11] 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:[12]

$$p_h^c - p_g^c = \kappa - \beta_n^*. \tag{1}$$

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

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

Finally, this household has a choice to live in the center or at the periphery with

[11]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.

[12]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".

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:

$$p_h^c = Y - \alpha \mathbb{P}(\beta_n^*) + e_h^* - \overline{V_h^p}. \tag{2}$$

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:

$$p_g^c = G + e_g^* - \overline{V_g^p}. \tag{3}$$

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 (2) and (3) in (1), and using the market clearing condition gives:

$$\beta_n^* = \frac{\kappa + G - Y + C + \overline{V_h^p} - \overline{V_g^s}}{1 - \alpha + 2C} \tag{4}$$

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. 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. Not modelled here a dynamism of the market potential of in some particular location, may have also played a similar role, abeit with multiple additional effects. Indeed 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.

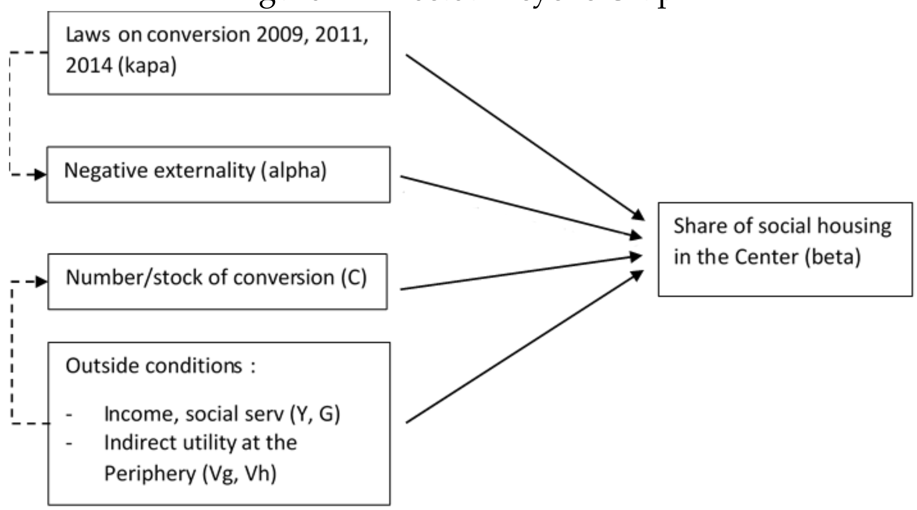
Obviously an higher effort of landlord to provide good-quality housing G, fosters the share of social housing. Furthermore, this parameter can be viewed as the effort of the central and local government to provide more funds and/or incentive to build more social housing. For instance in France, the 2000 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. This reduction of the risk for PDR is not modelled here but can be understood via an increase in G.

Finally an interesting result is that β_n is a decreasing function of the stock of unit that are converted C. Indeed 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, make this law more difficult to implement in the center due to the limited stock of conversion available.

2.3 Directed Acyclic Graph

The Directed Acyclic Graphs (DAG) in Figure 2 presents the determinants of the share of premises converted in social housing based on the previous formal model. Black arrows typically represents the determinants from the equilibrium Equation (4). From this model, to identify the impact of κ that affect the supply of conversion, we have to control for C that also affects the supply, and for several demand shifters that are $G - Y$, $\overline{V_h^p} - \overline{V_g^s}$ and α.

Figure 2: Directed Acyclic Graph



However, some of these controls are problematic. To illustrate this, dashed arrows represent some of the relationships that are missing in this model. First, "outside conditions", such as changes in the welfare at the periphery ($\overline{V_h^p}$), social housing services there (G), or changes in income at the center (Y), can also influence the total number of converted houses (C). These potential interactions between variables are just one example; we certainly omit some determinants that affect both the dependent variables and our control variables. For instance, controlling for α but not for all the other variables that affect β and α, creates a new pattern of bias, since α is considered in this DAG as 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. Our strategy is thus to introduce these controls progressively and to compare the result with a specification without these variables but with a rich set of fixed effects. By leading a regression discontinuity design at the border where these laws are applied, we also minimize the difference between what is called here the center and the periphery (e.g. $\overline{V_h^p} - \overline{V_g^s}$).

2.4 Data and descriptive statistics

Change of use (β)

The housing data is derived from the Land Registry Files provided by CEREMA (Center for Studies and Expertise on Risks, Environment, Mobility, and Spatial Planning), 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. The first available vintage is the housing stock as of January 1st, 2009, and is updated annually. These files provide the description and geolocation of all buildings and land parcels.

In this study, the land registry files enable 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.

Social housing units are defined by CEREMA as having social landlords as owners. However, this definition does not allow for the identification of all social housing units, as in some cases, they may be owned by private landlords. Another means of identifying social housing is by selecting units that benefit from tax exemptions. These exemptions are granted on the condition of being owned by a social landlord and/or being a rental property financed by certain state aids. However, these exemptions may be time-limited but the CEREMA indicates an average duration of 25 years for identifying these housing units, which is adopted in this study. The social housing units considered are those benefiting from a tax exemption as of January 1st, 2020, and/or having had a tax exemption in the 2009 housing stock. 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 is aggregated at the IRIS neighborhood level and corresponds to the number of square meters that have undergone a change of use. The results are separated for social housing units and residential units intended for private housing.

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 2019, which means that 10 more neighborhoods see changes in use towards social housing 13 years after the first observation.

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).

Airbnb

Airbnb data comes from the Open Data Soft platform, a French company that makes databases available. The data available 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. The data indicates that the last Airbnb account creation was in 2017. We have therefore restricted our analyses, for results including short-term rentals, to Paris intra-muros to 2017.

Income

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.

Reputation of secondary schools

Since the residential choice of household depends partly of the quality/reputation of school, we use indicators that measures the quality of secondary schools. These indicators, named "indicators of added value" (IAV) of secondary schools, measure the school's ability to support its students through to the baccalaureate, which is the first academic degree that grants the completion of secondary education. These indicators have a long history (Evain, 2020). They were created in 1987 by the French Ministry of Education to manage secondary schools. After an inadvertent leak in the media, they became public in 1993 and have since been regularly used to rank secondary schools by newspapers. 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.

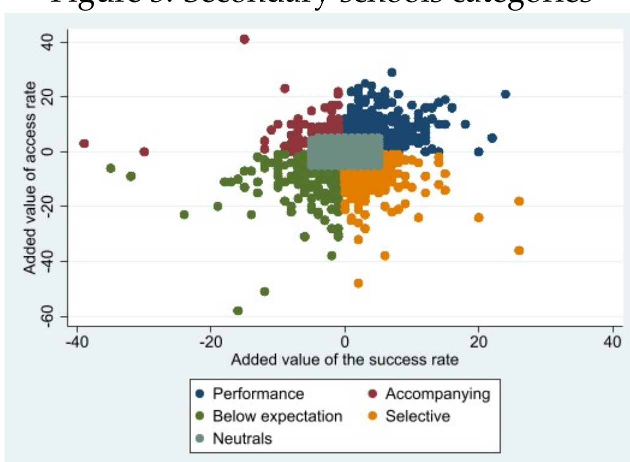
From this computation, the statistics department of the French Ministry of Education, hereafter DEPP (Direction de l'Evaluation, de la Prospective et de la Performance) categorize schools according to their added value in terms of success and access.

Schools can then be classified as “neutral”, “performance”, “accompanying”, “below expectation” and “selective”. Figure 3 represents these different categories along the success rate on the horizontal axis and the access rate on the vertical axis.

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

Since the methodology has changed over time, we cannot use the data from the start of our period. We limit our analysis to 2012 when considering these data. We select the nearest secondary school for each neighborhood.[13]

Figure 3: Secondary schools categories



[13]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 delimited effect of the law suggests a Spatial Regression Discontinuity design (SRD). However, a potential issue with SRD is the problem of compound treatments which occur when multiple treatments affect the outcome of interest simultaneously (Keele and Titiunik, 2015). One solution is to use the temporal discontinuity of when the policy of interest came into existence. This panel approach of RDD, called difference in discontinuity (Grembi et al. (2016)), hereafter diff-in-disc, enables to control for multiple treatments and time-invariant factors by time differenciation and fixed effects.[14] However, it requires that no other policies have been simultaneously implemented in the zone treated which is verified here. We estimate the following equation:

$$
\begin{aligned}
Y_{it}^{\flat} = exp(\lambda_i^{\flat} + \sum_j \varphi_j^{\flat} Z_i^{\flat} T_j + \sum_j \gamma_j^{\flat} Z_i^{\flat} D_i^{\flat} + \sum_j \delta_j^{\flat} D_i^{\flat} T_j \\
+ \sum_j \beta_j^{\flat} T_j D_i^{\flat} Z_i^{\flat} + \theta_t^{\flat} + \Gamma_{it}^{\flat}) \varepsilon_{it}^{\flat}.
\end{aligned}
\tag{5}
$$

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.[15]

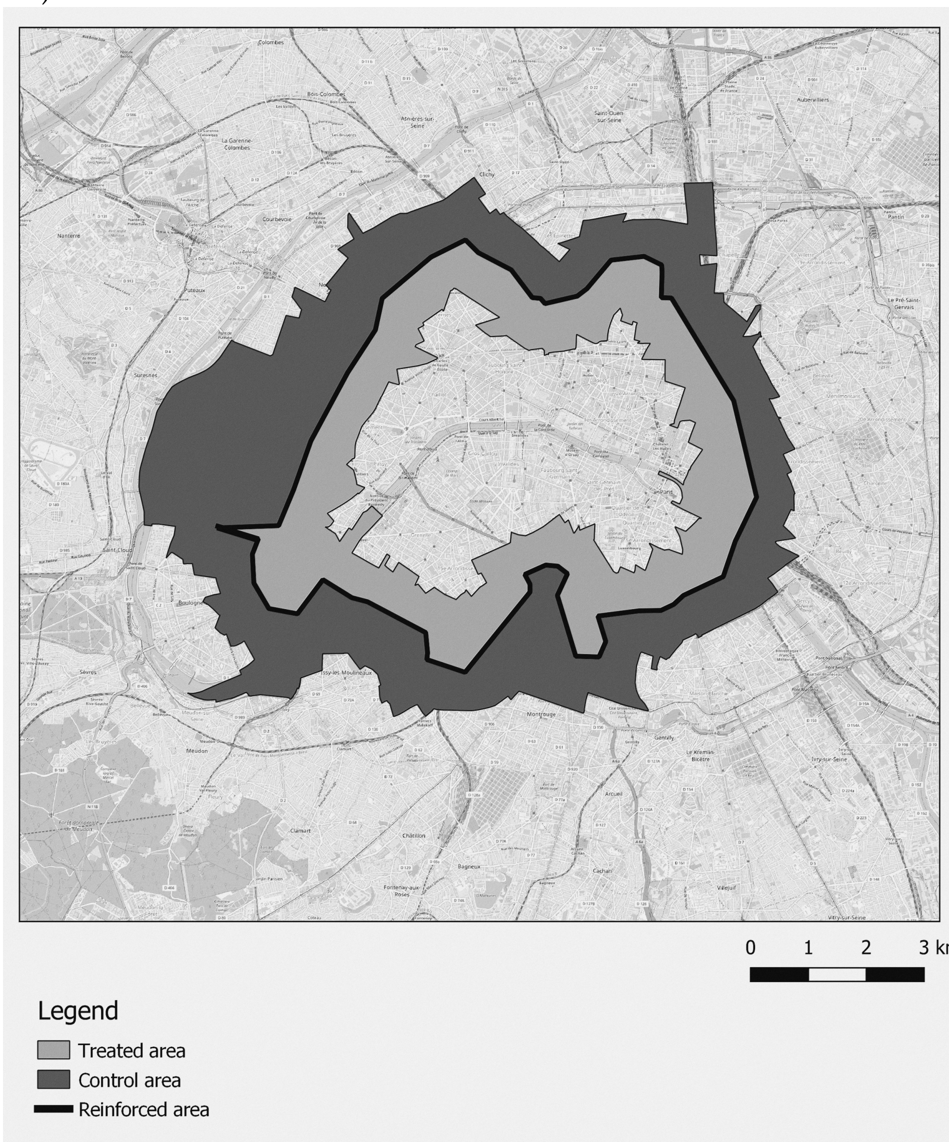
This dependent variable is delimited geographically according to a particular distance to the border treatment zone. For instance with a bandwidth $\flat = [-300, 300]$, 300 meters are taken on both side of the limit of the treatment area. We estimate this equation seven time by increasing this spatial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

Figure 4 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] See Eggers et al. (2017) for discussions.

[15] Similar results are obtained with OLS without all the observations of the dependent variable that are equal to zero, see Appendix D.

Figure 4: 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 $\beta^{\flat}_{2014}$ that provides the Local Average Treatment Effect (LATE) of the three compensation laws.

By examining the three estimates across various spatial windows, we aim to perform a 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 appendix 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 in the endogeneity of the zone, in particular the spatial discontinuity (the border line), may not be exogenous. Such a possibility is also unlikely 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 i.e. : $\sum_{i=1}^{N_{control,pre}} w_i^{sdid} Y_{it} \approx \sum_{i=1}^{N_{traited,pre}} Y_{it}$ 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:

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

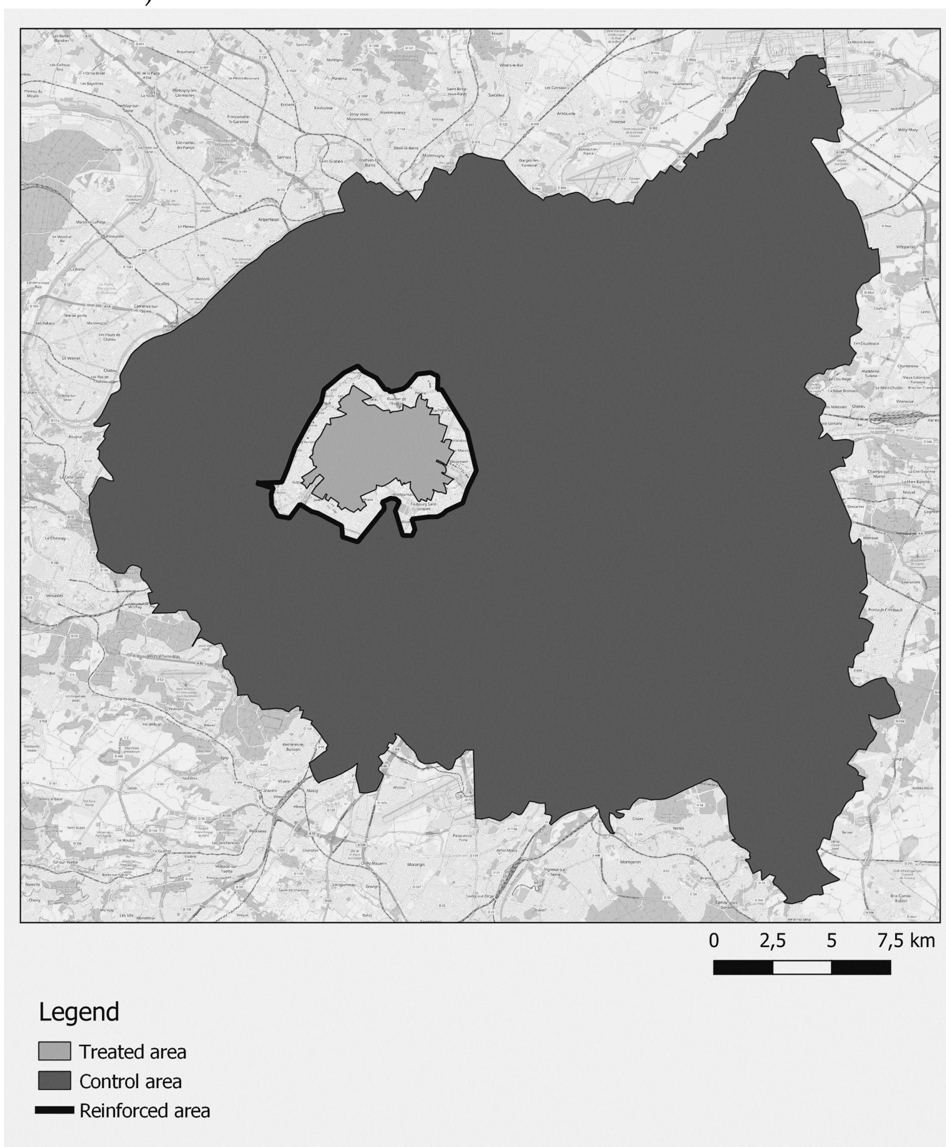
With η_i the neighborhoods, Γ_t the years, ϵ_{it} the error term and Y_{it} the dependent variable. The weights used to build the synthetic controls are presented in the appendix.

The SDID strategy is still estimated from Equation (5) with PPML.

We conducted a series of estimations by considering the same set of treated districts than in the previous analysis, namely with distance from the border of the reinforced area using the positive bandwidth presented previously. The aim is here to provide results that are directly comparable with those presented until now. We refer to this empirical strategy as the "border" 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 4, while the untreated are selected in the dark gray area of the Map 5 below.

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



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 B for five additional ones) and various weight distributions. These findings shed light on 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. The 2014 reform appears to have a smaller effect, with a coefficient ranging between 0.4 and 0.5.

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

In contrast, no matter the assumptions made on the bandwidth, the 2009 law's initial implementation is not statistically significant. This finding may be attributed to the restrictive nature of the legislation, which stipulates that changes of use must occur within the same district. This type of policy can have heterogenous spatial effect. Indeed, since the number of converted premises is higher at the border where the SDID is done (compared to central Paris), the constraint of doubling the floor space is not so restrictive. In addition, this law is implemented in the aftermatch of the financial crisis, it is thus likely that the numbers of premices have increase in that period, which may plays against the identification of the effect of the law. Our estimations include time effects that control for these shocks and also individual fixed effects to control for districts with structural difficulties, but not for time-individual varying effects. We then introduce the number of premices converted thay may influence the supply over time depending on the location (C) as well as other variables that influence the demand side such as the median income in the district (Y in the stylized model). As discussed at lengh in the DIAG section, these variables generale several problems (multicolinearity, endogeneity) and are thus analyzed successively to observe how our coefficients of interest (β and in particular β_{2009}) 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). To conclude, the unsignificant effect of 2009 may simply comes from the fact that this first law takes some time before to be effectively detected in the data. This implies that the stronger effect of the 2011 law, may in fact, includes some lagged effects of 2009.

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. In particular the median income may be a poor proxy of the market dynamics. In particular, the gentrification process that progressively make a location trendy cannot be captured by the median income. To take this demand effect into account, we use data on Airbnb. Indeed several articles have shown that short-term rentals cause a displacement of the poorest (Belloy, 2023) and fosters gentrification (Wachsmuth and Weisler, 2018). Obviously, 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 (Hackworth and Smith, 2001). Furthermore to consider another aspect of the location choice of household, we use a measure of the reputation and quality of schools. There is indeed a large literature that emphasize 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 explain why the quality/reputation of schools matters. Households have in particular access to the "added value" of each secondary school, which measure the performance of schools in comparison to similar establishments in terms of access and success (see data section). Since this indicator controls for the profile of each school, namely the rate of success of a school is compared to the predicted rate of success in this school, according to the social background and age of the school's pupils, questions about the endogeneity of this variable are not obvious.

Data on school added value and on Airbnb are unfortunatly not available for the whole period 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 are invariant over 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 now reproduce the same analysis but we change the control group, which is now a synthetic area of the treated one. This analysis is thus a robustness check of the previous one. Figure 6 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 6: Treated and Control Areas in the Synthetic difference-in-differences at the border (bandwidth: 600 meters)

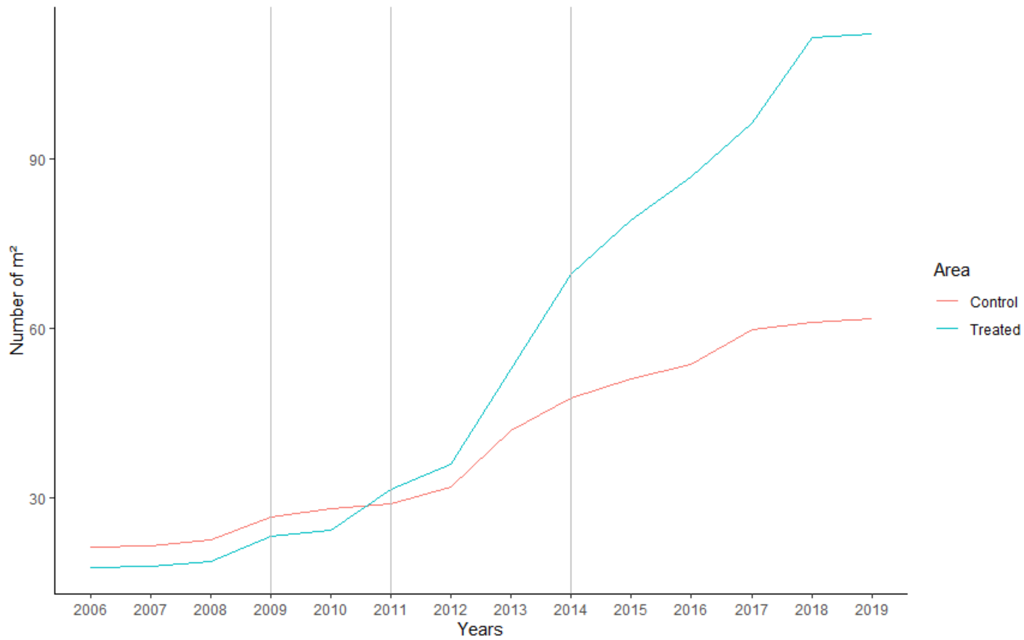


Table 4 presents the results of the synthetic difference-in-differences analysis, taking into account different distances from the edge of the compensation zone. Our findings reveal similar outcomes than in the previous section, with the 2009 law demonstrating no significant effect, while the 2011 and 2014 reforms successfully promoted the construction of social housing.

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 m^2). 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 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 m^2). Column (1) introduces the total number of conversions (in m^2), 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 (3.1.2) 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.

We refer to this empirical strategy as the "inner" 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 7 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.

Figure 7: Treated and Control Areas in the Synthetic difference-in-differences on the inner (bandwidth: 600 meters)

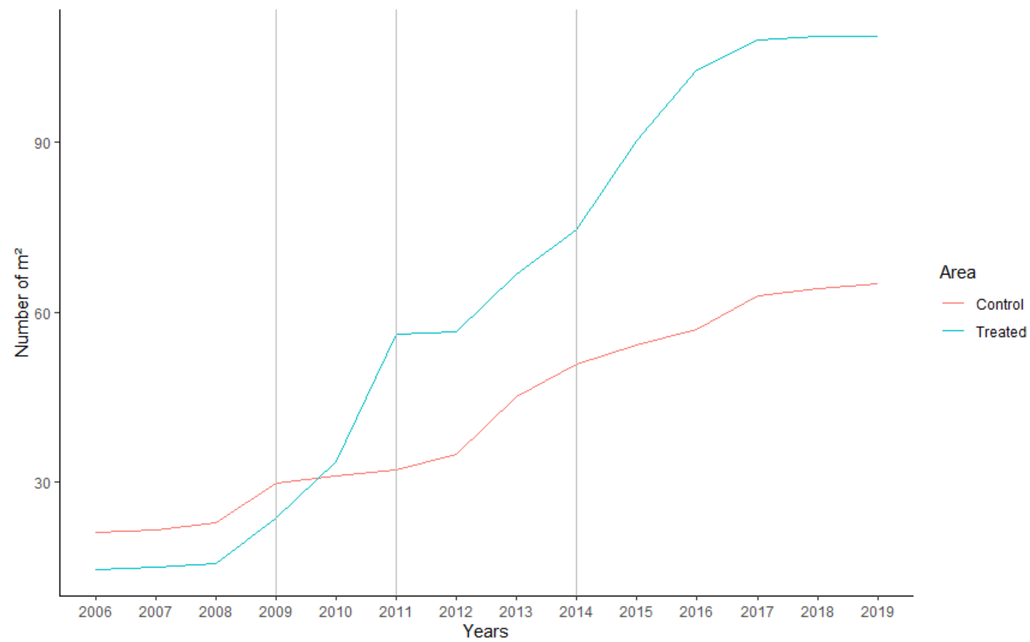


Table 6 presents the SDID results with different bandwidths. Our objective is to assess the distinct spatial impacts of these policies. The 2009 policy, by enforcing a compensation rule within each district, may exert a more substantial influence in the central areas compared to other reforms, mainly 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. Intriguingly, the coefficient 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 core is not significant. Appendix A 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).

Table 6: Social Housing Change from Synthetic Difference in Differences

Treated:	Inner						
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 Others effects

The effect of these different laws on other change of use is simple according to our theoretical model (see Equation, 4) . By rendering the development of public housing relatively more attractive, these urban policies are likely to generate an eviction effect regarding alternative redevelopments.

This is however a short run analysis which considers that the supply of change of use (C in the model) is fixed and not affected by prices. Indeed by reducing the stock of private housing that can be built from a change of use, these regulations make these locations even more valuable which may schift upward the change of use supply toward these destinations. As argued by Cheshire and Kaimakamis (2021) a premium for other development may exist and may even increase due to conversion law. At the equilibrium, if uses were not regulated, the marginal prices of other development once converted and the one of housing space would be equal. But an imbalance between the demand and the supply for each category can arise creating a price differential at the margin, namely a price premium. The size of this price premium would reflect the relative scarcity of the different categories of space, hence these differents laws by making the change of use for other developments more scarce can widen this premium.

To conclude while our model (but also regulators and jurists[16]) presents the eviction effect, there are economic arguments to consider that this regulation can have ambiguous effect on other developments, hence the interest of an empirical investigation.

We successively analyze the effect on other redevelopment, on price and on indicator of social diversity.

5.1 Additional data

Price

The real estate price data 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. 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.

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 in the last section to study the effect of the 2014 compensation law.

[16]For instance, commenting the 2014 law, Morel (2017) writes "This requirement of a minimum surface of compensation of 50% in the district results in the current near-impossibility of to carry out other transformation operations, in particular in the 1st, 7th and 8th arrondissement where change of use is already in short supply".

Socio-economic indicators

The data on the distribution of socio-professional categories is derived from the INSEE (National Institute of Statistics and Economic Studies) census for the years 2006 to 2019 in each IRIS neighborhood. The local entropy index is calculated based on the Theil and Finizza (1971) index and is computed as follows:

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

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.

The other index used is the location quotient (Isard, 1960) and is 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 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.

5.2 Supply of redevelopment in private housing

We replicate here the earlier analyses with the SDID method[17] with a simple alteration of the dependent variable; we now take into account other changes of use.

Our prior findings indicated that only the 2011 and 2014 laws exert a significantly positive impact on public housing development at the internal border of the

[17] We do not find convincing pre-trend for the diff-in-disc, see 6 in Appendix C, which lead us to give up these estimations for other redevelopment.

compensation zone. Consequently, a simple eviction effect should lead to a substantial adverse effect of these policies on other changes of use. On the opposite, if these laws lead to a price premium for other development, we should observe a positive effect. Table (8) reports the results. The eviction effect is clearly rejected for the 2009 and 2011 laws which have fostered other redevelopment, but 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 (20xx-20xx), a significant reduction in other development is observed. This last law has reduced the opportunities of other redevelopments. One can also observe that the Airbnb variable is significant, short-term rentals stimulates convertion toward other redevelopment than social housing.

Table 8: Other redevelopments

Method	Border		Inner		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).

Due to data limitations, we cannot test the effects of all these laws on prices for 2011 and 2009, but we can perform such an estimation for the year 2014. We observe a positive significant effect in Table (9).

A plausible interpretation that reconciles these 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. However, by 2014, the "2:1 rule" had become extremely binding, drastically limiting opportunities for compensation in cases of conversion to private housing. 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. Therefore, in central Paris, this most recent regulation has hindered conversion to other forms of redevelopment without encouraging conversion to HLM. This could be perceived as a policy failure.

Table 9: Housing price

Type	Border		Inner	
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 aim of these various compensation rules is to preserve housing for long-term residents in Paris. By encouraging the development of social housing, a certain social mix could be encouraged. In Table (10) we present the effects of these housing regulations on the location choice of different social-economic categories by distinguishing execute/managers and workers.

Table 10: Location quotien- Border

Type	Managers				Workers				Hloc	
	Location quotien		Share		Location quotien		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 managers 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).[18] 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.[19] The 2014 law seem to increase the share of workers (Columns 7 and 8).

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 managers, 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.

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

[19]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- Inner

Type	Managers				Workers				Hloc	
	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 managers 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.

To complete the analysis of inequality, regressions are run again with the interdecile 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	Border		Inner	
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[20] 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 policy

[20]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.

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,[21] 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 law was viewed as too restrictive, or, in the absence of any evaluation, it was considered ineffective. Regardless of the reason, the 2011 law completely relaxed the district compensation constraint. 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. Moreover, this law, while restrictive in the center but not at the fringes of the policy area, did not yield any significant results at the periphery.

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.

Finally, our analysis of these laws' effects on other forms of 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 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 gentrification. While we do see a decrease in managers and an influx of workers in response to these laws, we observe no significant effect on social diversity indicators.

Although our analysis presents a relatively strong internal validity, it obviously

[21] The website of the candidate, Bertrand Delanoë, is no longer online but can be accessed via waybackmachine: http://web.archive.org/web/20080118165802/http://bertranddelanoe.net/vlog-paris/le-projet-2008-2014/6-defis-prioritaires-pour-paris/se-loger-a-paris-un-droit-un-defi-une-priorite-absolue/

lacks the external one. While we can confidently assert that the redevelopment policies aimed at social housing have had no significant impact on gentrification 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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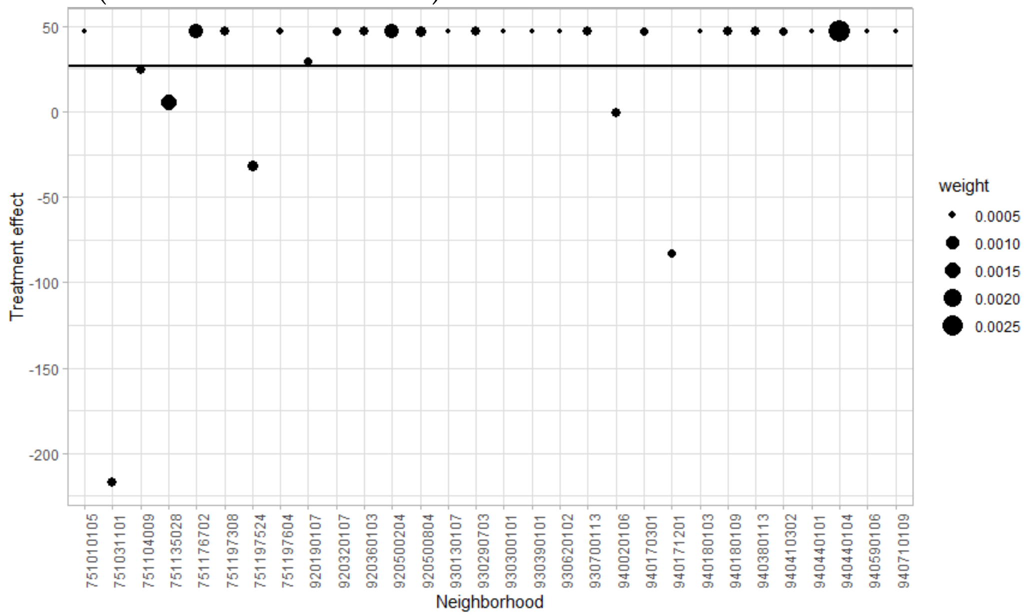
Appendix A

The weights used to build the synthetic controls are presented in Figure 8 and present relatively few extreme values.

Figure 8: Weights of the top 30 neighborhoods in the Synthetic Difference-in-Differences (bandwidth: 600 meters)



Appendix B

Table (13) provides the main results of the Diff-in-Disc for the different bandwidths. Table (15) the border estimation with the SDID and (**??**) the inner estimation still with this estimator.

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Appendix C

In Section 5.2 we do not lead again the diff-in-disc estimation since pre-trend are rather unconvincing as illustrated by Figure 9.

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 - Border 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

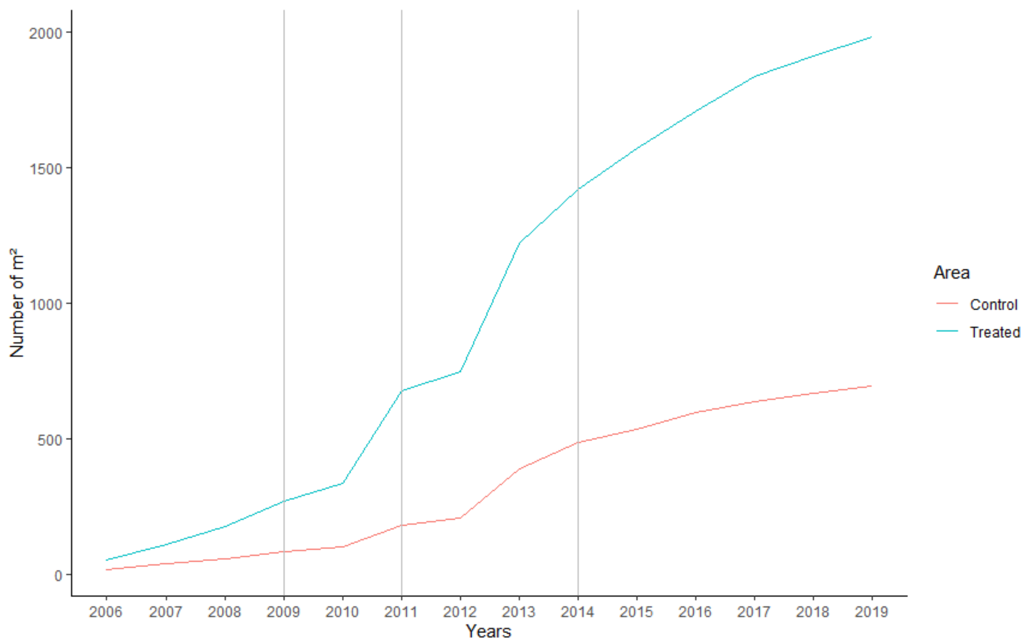
Robust standard errors in parentheses; a $p<0.01$, b $p<0.05$, c $p<0.1$

Table 15: Difference in Differences of Social Housing Change - Inner 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

Figure 9: Treated and Control Areas in the Difference-in discontinuities for all other changes of use (bandwidth: 600 meters)



Appendix D

Estimates have been made using the OLS method to compare results, but these estimates do not appear to be optimal due to a large number of zeros (see section 2.4). The other estimates are based on PPML in order to take these zeros into account. In contrast, weights are calculated using a synthetic difference-in-differences model developed by Arkhangelsky, which calculates weights parametrically and linearly. This technique can sometimes bias the estimates, but the results show a parallel trend for the different estimates. A non-parametric method has been developed within the framework of the synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010). This is 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 zone (see Figure 10). The results indicate an optimum bandwidth of 1. Figure 11 shows the results of the counterfactuals generated with the non-parametric method, with errors between the observed and control elements. 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 11), the counterfactual appears to follow the treated observations in the pre-processing period. Finally, Figure 12 shows the synthetic difference-in-differences method, which is the chosen method. This time we observe that the treated and control observations are parallel in the pre-treatment period.

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.

Figure 10: Optimal bandwidth for the non-parametric synthetic control method

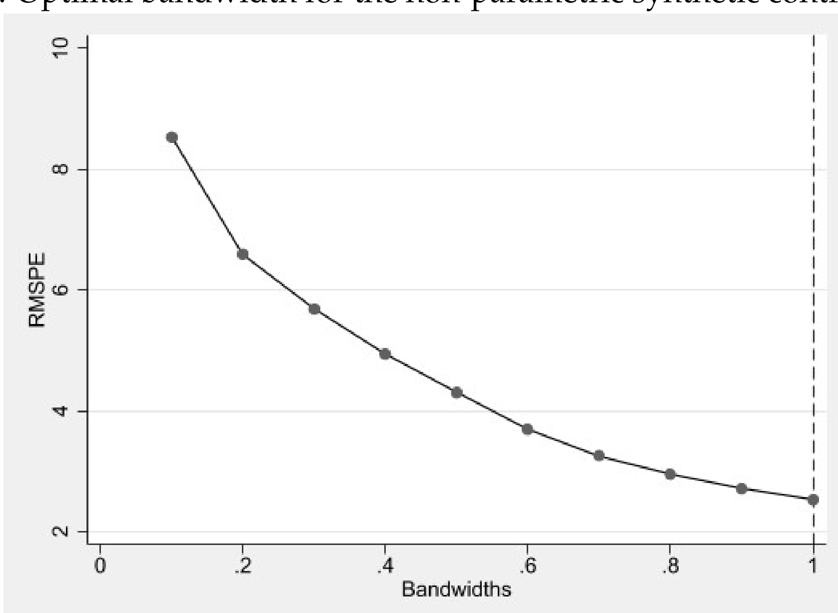


Figure 11: Non-parametric synthetic control method

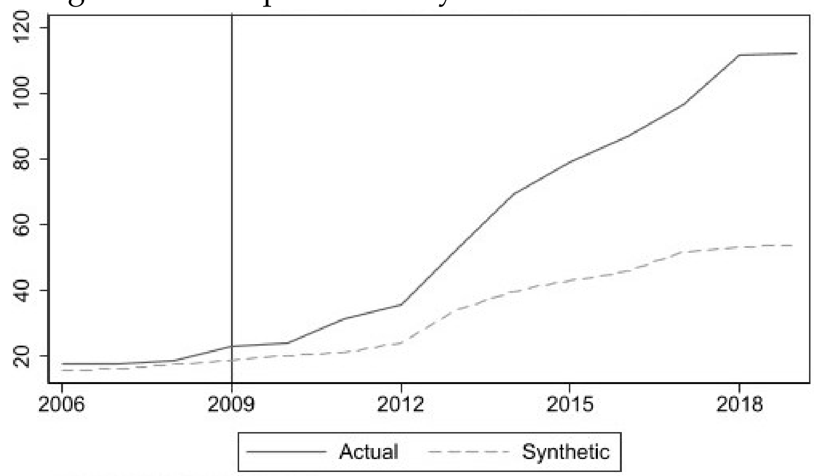


Figure 12: Synthetic control method

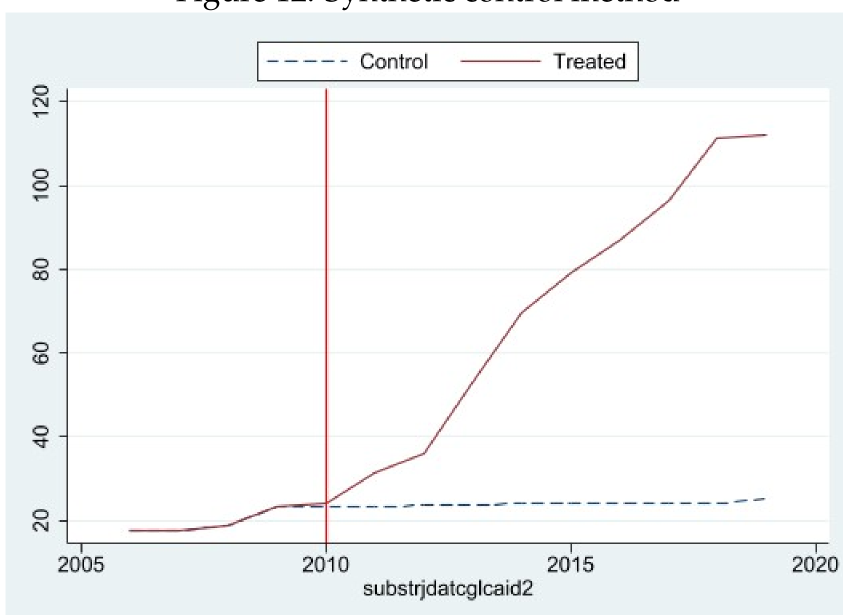


Figure 13: Synthetic difference-in-differences method