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# Evaluating Urban Renewal Policies: The Impacts of the PNRU Program on the Distribution of Income within Deprived Neighborhoods in France

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# Main contribution

1. **This study contributes to a growing literature that studies the impact of the National Urban Renewal Plan (PNRU) in metropolitan France.** Within the framework of the academic work of Nina Guyon and Camille Hémet, this study offers novel insights into the impact of the PNRU on the income distribution within renovated neighborhood over a period starting from 2002 to 2019. This research builds upon the pioneering work of Guyon (2016), who conducted the initial comprehensive assessment of the PNRU's effects on infrastructure and population dynamics up to 2013. Unlike Guyon's study, which relied on the Filocom database, I utilize income data sourced from INSEE. This allows for a direct comparison of our findings and facilitates an examination of their coherence.

2. **This study adopts a unique approach by focusing on income distribution within renovated neighborhoods.** Contrary to most papers which focus on income inequality *across* neighborhoods, I pay particular attention to inequality *within* neighborhoods. As the PNRU aims to change the social composition of deprived neighborhoods, I contend that this granular level of analysis holds significant importance. I posit that the impacts within neighborhoods are equally compelling as those observed at the citywide scale. To measure inequality, it employs inequality indices such as the Gini index and the inter-decile ratio. To have a better grasp of the underlying mechanisms influencing income distribution, I then utilize the median income per consumption unit, as well as the first and last deciles of income per consumption unit.

3. **I draw upon new estimators emerging from the academic literature by utilizing Callaway and Sant Anna (2021) estimator.** This econometric method advocated in recent academic literature takes into consideration staggered treatment dates.

4. **This research accounts for heterogeneity in the treatment.** Given the extensive scope of the program and its multifaceted goals, I ensure the robustness of my findings by examining the effects on specific subgroups. Consistent with Guyon (2016) and the recent report published by France Stratégie and Guyon (2024), I observe that neighborhoods with extensive demolition and reconstruction activities experience the greatest impact. The neighborhood classification categorizes neighborhoods into three distinct groups, enabling the assessment of the different types of neighborhoods which benefited most from the PNRU program. I ultimately evaluate the impact of the PNRU program in the four biggest French cities.

# Introduction

The large housing estates (“*grands ensembles”* ) in France, built mainly in the 1950s and 1960s, aimed at addressing the housing crisis and the growing demand for affordable housing after World War II. These massive residential complexes were designed to provide large-scale housing that was quick to build and affordable, with the aim of resolving issues of overcrowding and unhealthiness in the old urban neighborhoods. Despite their commendable intentions, the large housing estates have brought about a series of urban and socio-economic problems. Their uniform design and concentration of often homogeneous populations have led to the formation of monofunctional neighborhoods, devoid of social infrastructure, local services, and adequate green spaces. The stigma associated with large housing estates, often perceived as areas of social and urban relegation, has contributed to their gradual decline. Resident disaffection, combined with inadequate management and lack of infrastructure maintenance, has led to physical deterioration of the estates, as well as a degradation of quality of life and a sense of isolation within the communities residing there.

In 2003, as a response to the housing and socioeconomic crises was adopted in France the Borloo law to engage in an unprecedented nationwide renewal urban program. The *Programme National de Rénovation Urbaine* (PNRU hereafter) is a French renewal program launched in 2003, which ended in 2021. This nationwide program is designed to revitalize underprivileged neighborhoods by fostering social diversity and addressing territorial inequalities between different areas and populations. To ensure the coordination of operations with local stakeholders, particularly public housing offices and municipalities, the National Agency for Urban Renewal (ANRU) was established. In total, 47 billion euros were mobilized between 2004 and 2020, with ANRU contributing 12 billion euros.[1] The program impacted nearly 4 million residents and brought about the transformation of approximately 600 neighborhoods through the establishment of 399 projects. More specifically, 153,990 housing units were demolished, 139,618 reconstituted, 340,906 were rehabilitated, and 339,552 housing units witnessed residentialization operations.

The designated neighborhoods encompass a majority of the 751 Sensitive Urban Zones (ZUS), identified by French public authorities as areas requiring concentrated urban efforts in 1996.[2] Additionally, 166 neighborhoods facing similar urban and socioeconomic challenges have been included in the program under the designation "Article 6." Prior to the program's inception, these urban zones exhibited a higher unemployment rate, lower average household incomes, and a larger percentage of single-parent families among their population composition.[3] The term "ZUS" therefore labels neighborhoods with well-defined geography

[1] These figures appear on the official ANRU website: https://www.anru.fr/le-programme-national-de-renovation-urbaine-pnru

[2]Except for the 24 in the French overseas departments. Note that moreover in 2014, the French government introduced a new framework: *quartiers prioritaires de la politique de la ville* (QPV). QPVs represent an evolution of the *Zones Urbaines Sensibles* (ZUS), broadening their scope to encompass a greater number of neighborhoods facing social and urban challenges.

[3] These findings have been demonstrated by Guyon (2016).

and social composition, including high-rise estates, degraded housing, and concentrations of low-income residents.

Through demolition operations, reconstruction, and rehabilitation of social housing, urban development, and other measures, this policy aims at influencing the population composition of neighborhoods to promote greater social diversity. This approach stems from the shared belief among many policymakers that the socio-economic environment in which an individual operates has a significant impact on their life trajectory and economic opportunities. Individuals living in neighborhoods with concentrated poverty tend to accumulate less economic and socio-cultural human capital. Their social network is limited, and their opportunities for professional integration are also restricted. Therefore, the desire for spatial income diversity could be a major determinant in solving the social issues prevalent in neighborhoods where poverty is overrepresented.

Contrary to most empirical studies that evaluate income inequality at the city or country level, I observe the evolution of income dispersion within renovated neighborhoods. I believe that a more socially diversified neighborhood is as important at the neighborhood scale than at the city one. In terms of education, children living in a more diversified neighborhood could benefit from a more diversified school which ultimately could improve their scholar achievements. I also motivate the importance of a socially diversified neighborhood at the neighborhood level for security concerns, cultural opportunities, expansion of the social network, and more.

In this study, my objective is to assess the causal impact of the PNRU law on income distribution within deprived neighborhoods that undergone operations under the PNRU program. I first utilize the Gini coefficient and the inter decile ratio for a measurement of income inequality. Changes in income inequality offer insights into the distribution of resources within a neighborhood, with a more equitable distribution being desirable. A Gini coefficient approaching zero described a situation where all individuals possess the same resources, which depicts an egalitarian distribution of income. Through the promotion of a more mixed neighborhood, I expect the PNRU to have reduced income inequality within renovated neighborhoods. To further analyze the underlying mechanisms of changes in income distribution, I use additional income variables (median, first and last deciles). The conclusions drawn regarding income distribution will eventually explain the extent to which the PNRU has contributed to reaching social diversity within neighborhoods. The aspiration for uniform resource possession among all residents is contingent upon the existence of income diversity within neighborhoods as well as the prevailing level of poverty there. For instance, this study concludes that within poorly renovated neighborhoods notably, the Gini coefficient decreases (it tends to zero) due to the departure of affluent residents following the implementation of the PNRU, which ultimately leads to increased low-income segregation at the neighborhood level.

My approach to identify the impact of the policy relies on a difference-in-differences analysis, comparing neighborhoods that underwent renovation under the PNRU program with similar neighborhoods that were initially eligible but never received treatment. I have a total of

529 treated neighborhoods and 410 control ones that I analyze from 2002 to 2019 included. I focus on metropolitan France. By controlling for neighborhood and year fixed effects, I utilize the implementation year of the law (2003) as the treatment date, while also considering the staggered start of renovation activities across different neighborhoods. Given the diverse contexts and varying commencement dates of renovations, I anticipate significant heterogeneity in treatment effects. To obtain unbiased estimates of the program's impacts within such a varied context, I adopt the recent methodology proposed by Callaway and Sant Anna (2021). To bolster the robustness of my analysis, I introduce subgroups subjected to varying types and intensities of interventions to control for heterogeneity in the treatment as well as a neighborhood classification. Ultimately, I measure the impact of the law within the four biggest French cities.

My analysis reveals a small though significant reduction in income inequality, with a Gini coefficient decreasing by .007 from a baseline equal to .365 on average over the post-treatment period. This effect is mostly attributed to temporary departures caused by the program but remains robust after accounting for variations in treatment effects. Notably, the impact is predominantly driven by the upper third of the most extensively demolished and reconstructed neighborhoods where the decline in the Gini coefficient is multiplied by three. Additionally, in the global treatment effects section, I find an increase in the first decile, and a decrease in both the median and the last decile per consumption unit. These findings argue in favor of a reduction in income distribution within neighborhoods. Using the neighborhood classification, I find that income values are more towards central values in highly demolished and reconstructed neighborhoods, resulting from the departure of both the poorest and the richest residents. On the other hand, within little renovated neighborhoods, I find a decline in the median income arguing in favor of an overall impoverishment of the neighborhood, mostly caused by the departure of the richest households. Finally, I find that the PNRU has reduced poverty within renovated neighborhoods located within big cities compared to all non-renovated neighborhoods, but these same renovated units were less gentrified than what they would have witnessed in the absence of the program when comparing them with neighborhoods only located in big cities.

# Literature review

My analysis and findings add to the extensive and expanding body of literature examining neighborhoods and governmental policies aimed at fostering urban development. This section thoroughly reviews relevant literature, highlighting existing studies on theoretical concepts central to this research, and delving into empirical evidence. While the emphasis is primarily on the French context, some references are drawn from the United States and other developed countries. Firstly, the focus is on literature attempting to elucidate the underlying mechanisms that contribute to spatial and income segregation. This foundational understanding sets the stage for exploring the promotion of socially diversified neighborhoods. Subsequently, the discussion transitions into empirical studies evaluating the impact urban renewal programs, in particular the PNRU law. To enhance understanding of the subject, I include some contextual elements in this section that are pertinent to the French urban context. The affiliation with a deprived neighborhood is frequently viewed as a stigma, a consideration that holds significance not only from an economic standpoint but also for other social sciences disciplines such as sociologists or urbanists. However, the reviewed literature refers exclusively to economic papers.

Firstly, for the successful promotion of socially diversified neighborhoods, urban planners need a deep understanding of the economic forces that inherently resist spatial integration. The most frequently cited causes include idiosyncratic preferences, local public good provision, and income differentials.

Tiebout's seminal article (1956) is widely acknowledged for its contribution to understanding how households self-select into neighborhoods within a metropolitan area. In this model, consumers are well-informed about local provision levels and prices, enabling them to relocate to a community that aligns best with their preferences for a local public good. Individuals thus arrange themselves into distinct neighborhoods based on shared preferences for the levels of local public goods provided by these different communities. This self-selection provokes a peer effect, where like-minded individuals with similar budget constraint end up living in proximity. Subsequent studies have built upon Tiebout's framework, with Vandell (1995) expanding it to introduce the concept of "heterogeneous neighborhood", corresponding to a geographically area within a broader urban setting where residents and housing units vary based on four categories: housing characteristics, neighborhood amenities, accessibility characteristics and resident attributes. Vandell's work suggests that these various factors contribute to the formation of neighborhoods with a concentration of residents who share similar attributes. Moreover, if one considers that residents' preferences for local public goods differ based on their individual characteristics, individuals sharing a specific characteristic are likely to outbid others to secure a neighborhood with the desired attributes. Even when preferences for these characteristics remain consistent among all homebuyers, households with higher incomes can afford to pay more for housing with the desired attributes. Consequently, this results in the clustering of high-income households near spatially defined amenities.

Both of these works are crucial for comprehending the inherent concentration of residents within a city. I will keep these crucial factors in mind during my research, operating under the assumption that the presence of shared attributes, income in this case, inherently contributes to spatial segregation. Additionally, I recognize that past urban initiatives may have exacerbated income segregation. Indeed, in the French context, the concentration of low-income households in sensitive urban areas is not solely the outcome of natural forces but rather the result of previous urban programs. Following the Second World War, in response to the housing crisis, French public authorities extensively built social housing in the form of large complexes featuring high-rise towers. Predominantly termed "*banlieues*", these neighborhoods diverge from the existing urban fabric and accumulate social and economic deprivation, leading to various crises. Affected by deindustrialization and economic challenges, these areas have become synonymous with high unemployment, subpar schools, and crime. Consequently, starting in the 1980s, public authorities opted to address this pressing urbanization issue through the implementation of the French city plan "*Politique de la Ville*".

Secondly, it is essential to comprehend the rationale behind why social diversity is a sought-after goal for urban planners. While this objective is a common pursuit in many developed countries, it holds particular significance in the French context, marked by the construction of "*grands ensembles*" that accentuate social segregation. However, for now, I will focus on the theoretical aspect to grasp the motivation behind urban renewal policies. Recognizing the costs and benefits associated with social segregation (or diversity) becomes imperative in justifying policymakers' intervention, especially considering that these interventions hinge on public contributions and involve substantial costs.

One widely shared assumption is about negative "neighborhood effect" on future life prospects for individuals concentrated in impoverished areas. This theory which emerged in the US (Wilson, 1987) has progressively acquired a French equivalent pointing out the negative externalities of residing in ZUS in France (Fitoussi et al, 2004). Indeed, residential segregation in sensitive urban areas is usually associated with concentrated poverty, high unemployment and crimes, lower educational achievement, and other negative factors. These neighborhoods have earned a negative reputation and have amplified the perception of associated agglomeration costs, deeming it socially undesirable. This phenomenon has prompted the advocacy for mixed neighborhoods, a strategy that intuitively appears suitable for tackling residential and income segregation by integrating lower and higher-income groups. Thus, one expected outcome of mixed neighborhood is a reduction in the disproportionate representation of poor households in these areas. The PNRU law aims to foster a change in the social composition of the ZUS through the arrival of new and upper social categories. However, it is fundamental to make the distinction between the enhancement of residents living conditions and the replacement of these residents with wealthier households pushing the poor further away from the city center, a phenomenon known as gentrification. Due to unavailable data at the individual level, the monitoring of the former residents in their new neighborhood and similarly the one of the new settlers is not possible in the framework of this study.

This study focuses on what could be considered as the first stage of the PNRU law, being the impact of the PNRU law on income segregation within neighborhoods. The second stage is the impact of a change in income segregation on crime rates, educational achievements, or labor market opportunities within and across neighborhoods. My focus will not extend to measuring these further potential (dis)advantages of social diversity. Nevertheless, in this section, I aim to consult the existing academic literature on these outcomes to substantiate this research. The recognition that empirical evidence showcases positive externalities in various areas of interest motivates my choice to gauge income distribution, laying the groundwork for subsequent evaluations.

I will be using the existing literature on neighborhood effect to back up the intuition that reducing income segregation within a neighborhood produces positive externalities. The measurement of such neighborhood effect has mainly focused on education, labor market access, crime, and housing market prices.

Aliprantis and al. (2015) conducted an estimation of the impact of the closure and demolition of highly concentrated public housing on crime in Chicago. Their findings indicate that the reduction in crime in the affected and neighboring areas significantly outweighed the associated increase in crime caused by the arrival of displaced residents in new neighborhoods. Similarly, Boggess et al. (2016) observe a positive impact on the crime rate for neighborhoods undergoing economic improvement. They note that gentrifying neighborhoods situated on the "frontier" of the gentrification process experienced significantly more aggravated assaults compared to gentrifying neighborhoods surrounded by areas also undergoing improvement.

In addition, research papers document the causal impact of location on the long-run outcomes of children. The most cited study is the Moving to Opportunity (MTO) experiment in the United States (Chetty et al, 2016). The authors have randomly selected families and have provided them with housing vouchers to relocate from high-poverty places to more affluent neighborhoods. They find that the program enhances college attendance and earnings while reducing rates of single parenthood when the relocation occurs before the age of 13. Findings are however negative during the adolescence age. The diminishing positive effects of relocation with the age of the child suggest that the duration of exposure to improved environments during childhood significantly influences long-term outcomes. Since then, other MTO experiment have been engaged and they lead to mixed results, suggesting that neighborhoods effects depend on a complicated set of factors. This is why Billings et al. (2022) have attempted to identify the scale and the channels through which neighborhood effects influence the most the long-run opportunities for children. This experiment uses administrative Danish data and reveals that neighborhood characteristics have a strong but local effect on education. Interestingly for this study, they also find that neighborhood income is not the best predictor for individuals' outcomes, contrary to unemployment rate or education achievements with stronger and more significant effects.

Besides, the PNRU is a place-based policy that implies the demolition of social housing units. In the framework of this study, I do not track individuals over time to evaluate their potential increased life opportunities. However, I acknowledge that this could present an intriguing avenue for further research to build upon Chyn's findings (2018) where he identified significant long-term benefits for children whose families were compelled to move to less disadvantaged areas following public housing demolitions. In addition, Chyn and Daruich (2022) compared the long-run welfare gains between a voucher program and place-based policies and concluded larger gains for the former. However, they point out that place-based policies enjoy stronger political backing.

Similarly, the existing literature documents the impact of neighborhood effect on labor market outcomes. Authors attempt to elucidate whether residing in impoverished neighborhoods worsen people's economic prospects and life opportunities beyond factors contributing to their initial poverty. Gobillon et al. (2011) measure the effect of location on finding a job in the Paris region and find that 70% of the spatial disparities in unemployment duration are captured by local indicators, correlated with spatial segregation.

A significant apprehension regarding the promotion of mixed neighborhoods is the challenge of assessing whether it genuinely improves residents' well-being by notably increasing their disposable income or if it merely facilitates gentrification. In the latter scenario, wealthier agents influx into a previously low-income neighborhood, outbidding them with higher rent payments, ultimately pushing the less affluent further away. This undesirable outcome fails to address the issue of income segregation; instead, it relocates the problem. Academic research has endeavored to clarify which of these two outcomes arises from urban renewal efforts. One variable of interest for such a measure is housing market prices. In France, there is a limited number of studies of this kind, although Chareyron conducted research on the impact of the PNRU law on the local housing market. Their findings indicate that the program did not result in a significant increase in housing values within the treated neighborhoods. However, the study does highlight an enhancement in the attractiveness of renovated neighborhoods, accompanied by a shift of housing units in these areas from lower-income to higher-income categories (Chareyron et al.,2020).

I have developed a comprehensive understanding of the evidence related to the impact of socially mixed neighborhoods on various outcomes of interest. The current emphasis is on further exploring existing studies that specifically assess the effects of the PNRU law.

Before delving into this, it is essential to remind the reader that research on other urban French laws, such as the SRU law (Gobillon et al. 2014, Gobillon et al. 2022), is available. Both the PNRU and the SRU laws aim to address the problem of concentrated impoverished neighborhoods. However, there is no research in the current literature which assesses the complementarity of both laws, impeding a comprehensive understanding of the overall effectiveness of French urban policy.

The main paper of reference is Guyon's report, extensively evaluates the effects of the PNRU law on housing and social composition (Guyon, 2016). I will refer to this multiple times in this study. To the best of my knowledge, this is the only academic report offering such a detailed assessment of the PNRU law on income segregation at the national level. The author notably examines the program's effects on the social composition of neighborhoods as well as the evolution of poverty, by comparing the changes in the 572 renovated areas between 2003 and 2013 with those in the 302 neighborhoods not targeted by the PNRU. The econometric method of differences in differences is also employed for this analysis. The author notes that ZUS concentrate a significant amount of social housing, a phenomenon that is even more pronounced in the treated neighborhoods, particularly those witnessing more destructions. Moreover, poverty is overrepresented in these areas, with over 40 percent of households belonging to the first income quartile on average. Distinguishing between the private and social housing sectors, the author observes an increase in poverty in the private sector over the period, while it has decreased twice as much in the social housing stock. This observation is mainly attributed to the program's demolition aspect, leading low-income residents to relocate and mechanically reducing the poverty rate. Another critical consideration is the relocation of social housing, primarily done in other ZUS which could potentially be negatively affected by the law. Extending the evaluation timeline to 2019 will enable us to discern whether the observed trends have undergone modification.

The PNRU law involves an initial phase of demolition followed by reconstruction for almost 9 out of 10 renovated neighborhoods. Consequently, for a given period of time, individuals must leave their dwelling. Monitoring population displacement is challenging due to a lack of available data at the individual scale, resulting in a gap in the literature regarding a comprehensive analysis of the impact of demolition on population movements. After the conduct of surveys, the ANRU indicates that 128,500 households were to be rehoused in all of the PNRU projects, including around 119,000 from social rented housing to be demolished. 58% of households rehoused were rehoused within ZUS, and more than half of them on site (51%)[4]. Nearly 9 out of every 10 households rehoused were rehoused in their commune of origin. In this study, I am not able to challenge these figures. However, Lelévrier (2010) offers a limited analysis of these effects based on data from the Parisian metropolis between 2004 and 2007, focusing on a few specific operations. The analysis of mobilities induced by demolitions highlights a paradoxical dual effect: an accelerated departure of households with slightly higher incomes and a re-concentration effect, involving both staying in the same municipality and socially similar contexts. He also points out that relocations are socially selective: vulnerable individuals tend to stay in the same neighborhood and relocate to existing buildings with affordable rents, while higher-income households with fewer children are more likely to access new or less stigmatized housing in the neighborhood.

# Data

## ANRU

This set of data is sourced from successive waves of surveys realised by the ANRU in 2015, 2018, 2020, and 2021. This dataset furnishes specific details about the operations undertaken in the treated neighborhoods. I identify neighborhoods using a stable code, to define the treated sample as well as the treatment date using the starting year of operations, and ultimately the code and the share of IRIS overlapping the neighborhood that will then be used for weights. Besides, utilizing factors such as the nature of operations, amount of money raised per operation, number of housing units engaged per operation, I am able to classify neighborhoods in terms of intensity of treatment and distinguish the different natures of treatment. Overall, the data consistently demonstrate stability over time. However, when data were inconsistent, I usually favor the most recent waves assuming that the ANRU had a better knowledge of the accomplished work in 2020 than before. This is notably the case for budget variables that were often adjusted downwards after 2018.

[4] To consult the ANRU quantitative report: https://www.anru.fr/sites/default/files/media/downloads/2023-bilan_pnru_web_planches.pdf

## Geographical data

For a spatial measure of the evolution of the selected dependent variables I use a unique neighborhood identifier. As I utilize income data provided by the INSEE at the IRIS level, the second main geographical variable is the IRIS code. INSEE proposes a sub-municipal division called IRIS which is applied to municipalities with a population of at least 10,000 inhabitants, as well as most of those with populations between 5,000 and 10,000, which are subdivided into IRIS. These serve as the basis for disseminating sub-municipal statistics, representing a partition of the territory of these municipalities into neighborhoods of approximately 2,000 inhabitants each. As ZUS belong to urban areas they all have a corresponding IRIS code. I have thus selected this geographical scale, though aware that more precise geographical scales exist such observations at the cadastral section level.[5] For the analysis to be at the neighborhood level, I have aggregated IRIS codes that represent at least 1% of the neighborhood total area. In general, neighborhoods are bigger than IRIS but it does happen that 1 IRIS intersects more than 1 ZUS. In total 210 out of 939 neighborhoods are concerned with this case of one IRIS intersecting more than one ZUS. This can lead to spillover effects where the effect of the treatment on the treated neighborhood can affect a control neighborhood which is geographically close. In this study I do not address this issue and note that this is a major point to improve my analysis. Another limit to the data selection method is that I merge panel data with IRIS code that I considered stable across time. However, it happens that a same IRIS code corresponds to different geographical territories between two or more years, or that the share of intersection between the IRIS and the neighborhood evolves. However, IRIS are recommended in statistical analysis for being robust and stable across time. I therefore assume these are marginal cases.

## Income Data

I utilize open source INSEE databases to analyze income distribution. From 2002 to 2011, I use localized household tax incomes expressed at consumption unit level (*Revenus Fiscaux Localisés*). These figures were compiled from exhaustive files of personal income tax and council tax returns supplied to INSEE by the *Direction Générale des Impôts*. Since 2012, the *Fichier Localisé Social et Fiscal* (Filosofi) has replaced the *Revenus Fiscaux Localisés* and *Revenus Disponibles Localisés* systems. From 2012 to 2019 I therefore use the distribution indicators for declared household income per consumption unit from Filosofi. All income variables are reported gross income which correspond to the sum of the resources declared by the taxpayers on the income tax return, before any deductions.

### Variables

I conduct regression analysis on the number of households within the neighborhood. Since income variables are expressed per consumption unit, it would have been more precise to regress on the number of consumption units. This approach would have facilitated a clearer

[5] Data at the cadastral section scale requires access to the CASD - Secure Data Access Centre.

understanding of the correlation between resident departures (consumption units) and changes in income distribution within the neighborhood. However, due to the absence of a consumption unit variable in the Filosofi database, I resort to using the number of households as the nearest available variable. While this substitution lacks precision, as a consumption unit provides insights into household composition, the two variables remain fairly comparable. I assume that households are uniformly distributed within each IRIS even though housing units and relatively poorer residents are more concentrated on average in the overlapping area than in the rest of the IRIS. [6]

I categorize the variables of interest into two groups: initially, I regress on the inequality index to assess the policy's causal impact on income inequality. Subsequently, I examine income variables (D1, Q2, D9) to gain insight about income distribution within neighborhoods. When interpretating these variables, I will be mentioning their values in euros, e.g. a decrease in the first decile corresponds to a smaller amount of money earned by the poorest 10 percent. For all variables, I use indicators of the distribution of declared household incomes per consumption unit from INSEE. The fiscal income expressed per consumption unit has the advantage of taking into account the various compositions of households and thus the economies of scale associated with group living. The study compares income levels between multiple areas and analyzes income inequality and diversity among households within an area. The use of income adjusted for the number of household consumption units is therefore recommended because it becomes an income per “adult equivalent”, comparable from one location to another and between households of different compositions. It is calculated by dividing the household income by the number of consumption units it comprises. All individuals belonging to the same fiscal household have the same declared income per consumption unit. The number of consumption unit is defined as follow[7]:

$$\text{Consumption unit} = 1 + 0.5\,(\text{NA} - 1) + 0.3\,\text{NC}$$

The analytical boundary of income per consumption unit arises due to the internal nature of household consumption decisions. This metric suggests that households with identical compositions and incomes are comparable, yet they may reside in different areas with varying purchasing power, resulting in differing effective incomes.

First, I measure the causal impact of the PNRU policy on inequality index. I use the Gini index and complement it with the inter-decile ratio. The Gini index of fiscal income per consumption unit is an indicator of the degree of concentration of fiscal incomes per consumption unit among individuals in the studied area. It ranges between 0 (minimum concentration when all individuals have identical income) and 1 (maximum concentration when one individual holds all the income of the neighborhood). The inter-decile ratio (D9/D1) of the fiscal income per consumption unit establishes the ratio between the highest and lowest

[6] The same assumption is made in Guyon’s (2016) study.
[7] where NA is the additional number of adults and NC the number of children aged 14 or under.

income per consumption unit, excluding the top and bottom 10 percent of individuals with the most extreme incomes on each side. This indicator measures the relative disparity between the highest and lowest fiscal incomes, without being distorted by extreme incomes. It thus allows for the study of income disparities per unit of consumption within an area, as well as between areas.

I then turn to the median, the first and last decile of fiscal income. The deciles of income per consumption unit describe the distribution of income in 10% segments of the population. Consequently, the median constitutes the fifth decile. The second quartile is the median of the fiscal income per consumption unit. This variable divides people into two groups: half of the individuals belong to households declaring an income per consumption unit lower than this value, and the other half presents an income per consumption unit higher. Therefore, this indicator measures the central level of income per consumption unit within an area. Unlike the mean, which is sensitive to extreme values, the median is a more robust statistical indicator. The first decile (D1) of income per consumption unit is such that 10% of the population belong to households declaring an income per consumption unit lower than this value, while 90% have a higher income. The last decile (D9) of income per consumption unit is such that 90% of the population belong to households declaring an income per consumption unit lower than this value, while 10% have a higher income.

**Weighting**

The variables of interest are defined at the IRIS level. To ascertain the values of the dependent variables at the neighborhood level, I employ two weighting mechanisms. I use the share of the IRIS area to allocate the number of households at the neighborhood level. Secondly, I utilize the share of the neighborhood that intersects the IRIS to adjust income indexes and income variables at the neighborhood level. For instance, if a neighborhood is composed at 30 percent of IRIS 1 with median revenue $y_1$, and at 70 percent of IRIS 2 with median revenue $y_2$, the income at the neighborhood level is such that $y$ = $0{,}3y_1$ + $0{,}7y_2$, representing the weighted mean of the medians. While this approach may seem less intuitive, the unavailability of mean values at the IRIS level before 2011 necessitated this method, precluding the calculation of a more straightforward mean of means.

I put equal weight to all neighborhoods despite differences in the number of households an IRIS is composed of. I could have assigned to each neighborhood a different weight based on its population size: neighborhoods with larger populations would have more influence on the calculations than those with smaller populations. Thus, the unit of analysis is the neighborhood (and not the individual level).

## Sample Definition

The sample is made of 939 neighborhoods. These neighborhoods correspond to sensitive urban zones labeled in 1996 and are suburban territories defined by public authorities to be the priority target of urban policy, based on local considerations related to the difficulties experienced by the inhabitants of these territories. The selection process for local renovation projects seems somewhat ambiguous. Not all underprivileged areas were recommended for renovation by local authorities. However, upon reviewing the descriptive statistics depicting the socioeconomic status of ZUS, it becomes apparent that the chosen neighborhoods were left in even more impoverished urban and social circumstances. Other neighborhoods with particularly worrying socioeconomic parameters are also selected as beneficiaries. They are referred as "Article 6" neighborhoods because this specification appears in the article 6 of the law. For the sake of simplicity, I do not make distinction between both types of neighborhoods. Overall, 560 distinct neighborhoods benefitted from the PNRU program according to ANRU databases. When restricting the analysis to neighborhoods situated in metropolitan France, I encounter a reduction of 18 neighborhoods. Subsequently, upon selecting for treated neighborhoods with completed operations in 2019, I observe the loss of an additional 9 neighborhoods, which are subsequently included in the control group. Further, upon merging the ANRU databases with the reference table of ZUS, accounting for weighting coefficients, I experience the loss of an additional 4 treated neighborhoods. Consequently, our final dataset comprises 529 treated neighborhoods (including ZUS and those designated under Article 6) and 410 control neighborhoods (limited to ZUS only). Notably, control neighborhoods, by definition, have not undergone any interventions under the PNRU program.[8] The large number of untreated neighborhoods reduces the sensitivity of the counterfactual to unobserved shocks. Likewise, the ample number of observations allows for the assessment of the robustness of our primary findings across various subsamples.

For all analysis not requiring income variables (identification of the nature of the treatment, measurement of the intensity of the treatment, regression on the number of households, etc.) the sample is made of these 939 neighborhoods. However, when cross-referencing them with the INSEE income databases, specifically using the IRIS code, 101 neighborhoods become unaccounted for. More specifically, IRIS codes belonging to the reference list of ZUS provided by the ANRU do not match IRIS codes of the INSEE databases more than five times (five years). In this case, I drop the IRIS that did not match resulting in the loss of 101 neighborhoods, 42 treated and 59 controls. I thus obtain a sample made of 838 neighborhoods, 485 are treated neighborhoods and 358 are controls. Besides, some IRIS reveal missing values attributed to adherence to statistical regulations aimed at safeguarding anonymity within sparsely populated IRIS areas: the disclosure threshold is established at 200 inhabitants or 50 households for income data dissemination. In this case, I computed an approximative value at the neighborhood level. A way to improve my study would be to regress on the same sample size.

[8] There are, however, construction and demolition projects taking place outside the PNRU program in control neighborhoods.

# Empirical Strategy

I rely on the difference-in-differences method to estimate causal effects of the PNRU policy in a non-experimental setting. I compare the evolution across time $t$ and units (neighborhoods denoted $n$) in terms of $y_{n,t}$ between renovated neighborhoods and never renovated neighborhoods – those which never witnessed operations under the PNRU program. The identification assumption posits that, conditional on fixed effects and controls, the trends in the variables of interest would have been the same in never-treated neighborhoods and in treated ones in the absence of renovation. This assumption implies parallel evolutions of outcomes under study. This hypothesis will be tested using estimates of the dynamic effects of the treatment before the start of the renovation. In practice, I want both groups to follow parallel trends before any treatment implementation. For such an observation, the control group must possess similar characteristics to the treated group to infer that it represents a pertinent counterfactual trajectory.

I utilize two different approaches, both based on the fundamental principles of canonical difference-in-differences analysis. Firstly, I introduce a static two-way fixed-effects (TWFE) model. Recent papers demonstrate the limits of the standard TWFE method in the presence of time variation in the treatment and propose alternative approaches such as the Callaway and Sant Anna estimator that I will be using.

## Static Two-way Fixed-effect (TWFE)

The TWFE regression is an advanced iteration of a canonical difference-in-differences approach, commonly employed in panel data analysis. The unit fixed effects control for unobserved heterogeneity across neighborhoods that do not change over time (e.g., location of the neighborhood). The time fixed effects on the other hand account for time-specific effects that uniformly affect all units over time (e.g. inflation), thereby reducing potential bias and improving the accuracy of the estimated coefficients. To interpret the fixed effects, one can state that in the absence of the PNRU law, income or any other dependent variables, is determined by the sum of a time-invariant neighborhood effect and a year effect that is common across neighborhoods. Controlling for many unobserved-but-fixed neighborhoods characteristics enables us to forego selecting any control variables. The equation,

$$Y_{n,t} = \alpha_0 + \gamma_n + \delta_t + + \beta_{n,t} \, Treat \times Post \; + \epsilon_{n,t}$$

regresses the outcome $Y_{n,t}$ on neighborhood fixed effects $\gamma_n$, time fixed effects $\delta_t$, an interaction of a post-treatment indicator with treatment status, and an independent error term $\epsilon_{n,t}$. In this DiD setup, I am interested in estimating the ordinary least squares (OLS) coefficient $\widehat{\beta}$ , interpreted as an overall effect of participating in the treatment across groups and time periods. The standard errors are clustered by neighborhood. In this study, I produce a neighborhood classification to control for heterogeneity of treatment effect adding interaction terms named $Subgroups$ (i.e., neighborhood with a high demolition rate). This specification gives us the following regression,

$$Y_{n,t} = \alpha_0 + \gamma_n + \delta_t + + \beta_{n,t}\, Treat \times Post + \theta_{n,t} Subrgroup \times Treat \times Post + \epsilon_{n,t}$$

where $\theta_{n,t}$ measures the additional effect of belonging to a specific subgroup compared to the treated group that does not belong to the subgroup. This estimation method relies on several assumptions:

**Parallel trends:** in the absence of treatment, observations in the control and treatment groups would have followed parallel trends after the treatment. This allows treatment to be assigned non-randomly based on characteristics that affect the level of the outcome of interest but requires the treatment assignment to be mean-independent of variables that affect the trend in the outcome ( $\epsilon_{n,t}$). In other words, parallel trends allow for the presence of selection bias, but the bias from selecting into treatment must be the same in pre-treatment period as it is in post-treatment period:

$$\mathbb{E}[Y_{n,post}(0) - Y_{n,pre}(0) \mid D_n = 1] = \mathbb{E}[Y_{n,post}(0) - Y_{n,pre}(0) \mid D_n = 0]$$

**No anticipation:** anticipation refers to the situation where neighborhoods would have had anticipated intervention and would have had adjusted their behavior for when the intervention actually took place. In this case, one can assume that the managers of social housing have emptied the units in anticipation of the demolitions. Anticipation can bias the estimated treatment effect if it leads to changes in outcomes before the implementation of the treatment. I thus assume that treatment is unanticipated such that:

$$Y_{n,pre}(1) = Y_{n,pre}(0)\ \forall\, n\ with\ D_n = 1$$

**Stable Unit Treatment Value Assumption (SUTVA):** the potential outcomes of any neighborhood are not influenced by the treatment assignment of other neighborhoods. In other words, it assumes that there is no interference between neighborhoods, and the treatment assigned to one neighborhood does not affect the outcomes of other neighborhoods. In the case of the PNRU law, some control and treated neighborhoods are geographically close. Thus the treatment effect on the treated units may affect the untreated units and eventually bias the estimates. For neighborhood n, I define the observed binary outcome as $Y_n \in Y = \{O, 1\}$, the observed binary treatment as $D_n \in D = \{0,1\}$, and the two potential outcomes that which only exist when SUTVA is satisfied, as $(Y_n(0), Y_n(1) \in Y \times Y)$.

**No heterogeneity in the treatment:** the treatment has a uniform effect across all units being compared, allowing for a reliable estimation of the causal impact of the treatment.

### Dynamic TWFE

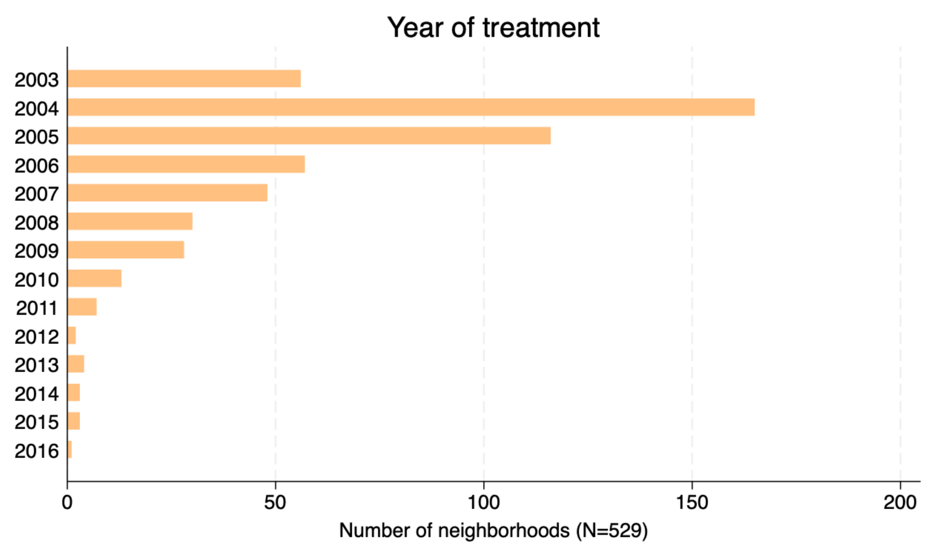
How does the effect of participating in the treatment vary with length of exposure to the treatment? This is a particularly relevant question in our study, as I would like to evaluate the lasting effect of the policy within treated neighborhoods. This is why I present here the dynamic TWFE,

$$Y_{n,t} = \alpha_0 + \gamma_n + \delta_t + \sum_{j \in \{-m,\ldots,0,\ldots,p\}} \beta_j \, Treat \times Post_{\ n,t-j} + \epsilon_{n,t}$$

where j is the time relative to treatment (e.g. j=1 in the first treated period for neighborhood $n$). The coefficients after the event has occurred ($\beta_j \ for\, j \geq 0$) capture the dynamic effects of the treatment as these effects manifest over time since the event. The dynamic TWFE is an intermediary step in our methodology presentation that allows to introduce time relative to treatment. However, like the static TWFE specification, the dynamic design with fixed effects fails to yield sensible estimates of dynamic causal effects under heterogeneity across neighborhoods treated at different periods. I therefore directly turn to most recent methods proposing remedies for staggered treatment timing mainly focus on the static specification and do not use dynamic TWFE.

### Issues with standard TWFE

In this study, I first use 2003, the year of the policy adoption as the treatment date for all neighborhoods. I then redefine treatment date as the year when the first work started in a neighborhood. Using this definition, neighborhoods are not all treated at the same period and treatment date significantly varies across neighborhoods (refer to Graph 1).




Graph 0.1. Year of treatment per neighborhood

A different timing in the treatment across neighborhoods is of fundamental importance as the recent academic literature has shown that TWFE model should not be used to highlight treatment effect dynamics notably.[9] I propose here a very simplified explanation of the problem with variation in the timing of the treatment across units. For a more detailed explanation, readers can refer to the emerging literature on issues using difference-in-differences with multiple time periods (Borusyak and Jaravel (2017), Goodman-Bacon (2019), de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and more).

**Problem 1: Comparing early treated with late treated units**

By doing a difference-in-differences I measure changes across time and changes across groups. Regarding the latter, in a setting with timing difference in the treatment, I compare treated with never treated units, treated with not yet treated units and ultimately later treated with earlier treated units. This last comparison is to some extent problematic as I use for controls (early treated) units that were already treated. More concretely, assume I have only two observations and that parallel trend assumption holds before treatment. If one unit gets treated earlier and the outcome of interest changes as a result of the treatment, I then obtain a new trend that is no longer parallel to the second unit. By the time the second unit is treated, it is incorrect to compare it with the first unit post treatment as the parallel trend assumption no longer holds.

**Problem 2: Negative weight problem**

This second problem is closely related to the first. When estimating ATT, I essentially compare treated units with untreated ones such that,

$$ATT = \sum w_1 \times Y(treated) - w_0 \times Y(untreated)$$

Treated units receive a positive weight $w_1$ while untreated units receive a negative weight $-w_0$, resulting from the substraction. However, when comparing early treated with late treated units, I attribute to the early treated group a negative weight such that,

$$ATT = \sum w_1 \times Y(treated) - w_0 \times Y(early\ treated)$$

TWFE put negative weights on some treated units because it uses them as controls. This can lead to problematic cases where the treatment effect is positive for all units, but the TWFE estimation result in estimates β that are negative. Besides, even in the absence of negative weights, the weights are still sensitive to the size of each group, the timing of treatment, and

[9] Treatment effect dynamics can also exist when the date of the treatment is the same for all neighborhoods and do not only concern event-study cases.

more, making its interpretation problematic. One must therefore be careful when interpreting the causal effect with a TWFE as it does not correctly identify ATT when the treatment effects are heterogeneous, and the timing of the treatment varies across units. [10]

### The Callaway Sant Anna Estimator (CSDID)

Recent approaches utilizing staggered designs offer significant advantages in addressing the challenges posed by the standard TWFE method. First, it provides sensible estimands even under arbitrary heterogeneity of treatment effects. In addition to preventing negative weighting, it allows to specify the weighting of effects across cohorts (i.e., in proportion to cohort size) rather than relying on OLS (i.e., in proportion to the variance of the treatment indicator). Secondly, it clearly identifies which units serve as a control group to infer the unobserved potential outcomes. This is in contrast to standard TWFE models, which often result in unintuitive comparisons under staggered timing. In this study, I selected the Callaway and Sant Anna estimator and provide a simplified explanation of their estimator. For a more detailed explanation, I invite readers to consult Callaway and Sant Anna (2021).

Callaway and Sant Anna provide a simple way to aggregate group-time average treatment effects into average treatment effects across different lengths of exposure to the treatment. They propose an aggregation scheme that is suitable to highlight treatment effect heterogeneity with respect to length of exposure to the treatment that does not suffer from the drawbacks associated with the event study regression. In staggered setups, a parameter that is interesting and has clear economic interpretation is the average treatment on the treated (ATT). Callaway and Sant Anna (2021) consider as a block the group-time average treatment effect on the treated,

$$ATT_{(g,t)} = \mathbb{E}[Y_{n,t}(g) - Y_{n,t}(\infty) \mid G_i = g]$$

which gives the ATT at time t for the cohort first treated in time g. For instance, ATT (2004, 2007) corresponds to the average treatment effect in 2007 for neighborhoods who first witnessed operations in 2004. Under the staggered versions of the parallel trends and no anticipation assumptions, I can identify $ATT_{(g,t)}$ by comparing the expected change in outcome for cohort $g$ between periods $g-1$ and $t$ to that for a control group never (or not yet) treated at period t,

$$ATT_{(g,t)} = \mathbb{E}[Y_{n,t} - Y_{n,g-1} \mid G_i = g] - \mathbb{E}[Y_{n,t} - Y_{n,g-1} \mid G_i = g'] \text{, for any } g' > t$$

[10] Consult this website for further information: https://friosavila.github.io/playingwithstata/main_csdid.html and Sant Anna's lecture on Difference-in-Differences Methods at https://pdhp.isr.umich.edu/wp-content/uploads/2023/01/DiD_PDHP.pdf

Since this holds for any comparison group $g' > t$, it also holds if I average over some set of comparisons $\mathcal{G}_{comp}$ such that $g' > t \; \forall \; g' \in \mathcal{G}_{comp}$,

$$ATT_{(g,t)} = \mathbb{E}[Y_{n,t} - Y_{n,g-1} \mid G_i = g] - \mathbb{E}[Y_{n,t} - Y_{n,g-1} \mid G_i \in \mathcal{G}_{comp}]$$

I can then estimate $ATT_{(g,t)}$ by replacing expectations with their sample analogs,

$$\widehat{ATT_{(g,t)}} = \frac{1}{N_g} \sum_{G_i = g} [Y_{n,t} - Y_{n,g-1}] - \frac{1}{N_{\mathcal{G}_{comp}}} \sum_{G_i \in \mathcal{G}_{comp}} [Y_{n,t} - Y_{n,g-1}]$$

Specifically, they consider two options for $\mathcal{G}_{comp}$. It either corresponds to never-treated units ($\mathcal{G}_{comp} = \{\infty\}$) or not-yet-treated units ($\mathcal{G}_{comp} = \{g' \colon g' > t\}$). In our case study I will be relying on the first option with never treated units.

In the results part, I will be interpretating graphs resulting from Callaway and Sant Anna estimator. It is important to note that the standard deviation tends to increase as I move further away from t0 in the positive direction. This increase occurs due to the diminishing sample size in neighborhoods treated later in the time sequence. Specifically, some neighborhoods treated at later dates may not have observations available for the effect at t+6 and beyond. For instance, a neighborhood treated in 2014 could have an effect observed at t+5 at most, considering that data extends only up to 2019. Therefore, the standard errors of treatment effects may widen as I move further away from the treatment initiation date, reflecting the variation in available observations across different time periods.

# Descriptive Statistics

This section is divided in two distinct subsections. The first subsection compares dependent variables in treated and comparison groups while the second subsection focuses on the nature of operations that occurred in the treated neighborhoods.

## Dependent variables

In this subsection, the pre-treatment dependent variables (number of households, inequality indexes, income variables) are compared between control and treated units. As the treatment date varies among the treated units, I can only use the year 2002 at which no neighborhood was treated (as the policy was implemented in 2003). The size of the sample varies as I lose observations with some variables. The maximum size of our sample is 939 neighborhoods for which I have area data. When merging it with datasets on operations I lose four neighborhoods, and the rate of mismatch increases when using INSEE databases. Overall, I have a minimum of 817 neighborhoods with 342 control neighborhoods and 475 treated ones.

On average, the number of housing units and household are bigger in the treated neighborhoods, but this is mostly explained by a bigger area. The density (unit: number of households per square kilometer) is on average the same in both groups.[11] Regarding income dispersion, I observe relatively comparable inequality indexes on average, although slightly more pronounced in treated neighborhoods with a higher Gini coefficient and inter-decile ratio. The median income per consumption unit is on average higher in the control group: half of the unit of consumption earned less than 10,768 euros per year (expressed in 2002 euros) compared to 9,739 euros in treated neighborhoods. Regarding income at the extremes of the distribution, the poorest 10 percent of consumption units earned on average less than 3,164 euros in control neighborhoods compared to 2,574 euros in treated neighborhoods. The richest 10 percent on average had an income above 21,681 euros annually in control neighborhoods compared to 19,840 euros in treated neighborhoods. Despite relatively comparable levels that allow to assess that groups are not statistically different, it seems that on average, treated groups have a slightly more disadvantaged socioeconomic situation than in the control neighborhoods. This pre-intervention difference demonstrates a neighborhood composition effect and justifies the existence of a non-random assignment where ANRU selected the most disadvantaged neighborhoods (from a panel of neighborhoods already considered disadvantaged).

**Descriptive Statistics: Control Units in 2002**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Number housing units | 408 | 1250.425 | 1704.258 | 4.239 | 20766.521 |
| Number of households | 366 | 1014.876 | 1325.445 | .312 | 14314.813 |
| Area | 410 | 394589.27 | 408685.56 | 3369.78 | 3146311.4 |
| Density | 366 | 3005.003 | 3273.278 | 7.345 | 26537.924 |
| Gini coefficient | 348 | .352 | .069 | .013 | .578 |
| Inter decile | 342 | .104 | .123 | .01 | .97 |
| Q2 | 351 | 10767.989 | 2882.823 | 0 | 18649.557 |
| D1 | 342 | 3163.565 | 1592.261 | 48.166 | 8980.126 |
| D9 | 348 | 21681.368 | 5360.669 | 715.918 | 42190.973 |

**Descriptive Statistics: Not-yet-treated units in 2002**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Number housing units | 527 | 2230.975 | 2583.474 | 2.246 | 29317.713 |
| Number of households | 507 | 1827.86 | 2032.117 | 5.346 | 19665.684 |
| Area | 529 | 638072.96 | 732845.58 | 6792.097 | 8141016.6 |
| Density | 507 | 3031.025 | 2433.086 | 40.197 | 24326.855 |
| Gini coefficient | 485 | .353 | .075 | .005 | .779 |
| Inter decile | 475 | .107 | .101 | .01 | .819 |
| Q2 | 487 | 9739.077 | 2768.324 | 123.899 | 26913.643 |
| D1 | 475 | 2573.551 | 1474.197 | 22.581 | 8587.767 |
| D9 | 485 | 19840.906 | 5106.21 | 259.475 | 57930.523 |

Table 0.1. Descriptive Statistics for Control and Not-yet Treated Units in 2002

[11] France Stratégie and Guyon (2024) indicate that unrenovated neighborhoods are less densely populated.

Although already convinced of the relevance of the choice of the control group due to the “ZUS” label held by the neighborhoods in both the control and treatment groups, these descriptive statistics in 2002 confirms the relevance of the selected control groups. To apply the difference-in-differences method, it is necessary for the control and treatment groups to follow parallel trajectories in addition to sharing similar characteristics in order to evaluate the causal effect of the PNRU law. These parallel trends are verified in the graphs presented in the results parts.

## Nature of the treatment

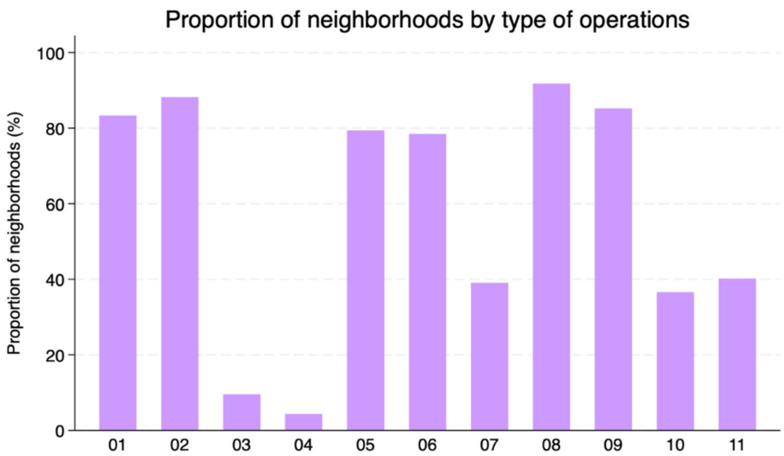
In this subsection, I provide an overview of the various operations conducted in the treated neighborhoods. I only retain neighborhoods where operations have been completed in 2019 and exclude operations that were canceled. This selection choice led to the suppression of nine neighborhoods from the treated sample that I therefore redirected to the control group. In metropolitan France, there is a total of 23,791 finished operations, all types of operations combined. Is treated a neighborhood which witnessed at least one of the following interventions, financed under the PNRU program:

| **Type of operations** | **ANRU subsidies (in million euros)** |
|---|---|
| Demolition of social housing | 2,320 |
| Production of social housing | 2,280 |
| Change of use of social housing | 9,1 |
| Requalification of degraded urban blocks | 135 |
| Rehabilitation of social housing | 1,150 |
| Residentialisation of social housing | 687 |
| Improvement of service quality in social housing | 98,8 |
| Urban planning | 1,640 |
| Public facilities | 1,170 |
| Commercial or artisanal spaces | 96,6 |
| Intervention on private housing | 248 |
| Project Management / Engineering | NA |

Table 0.2. Type of operations

The PNRU policy ambitions to transform neighborhoods landscape. Table 0.2 presents a total of twelve distinct types of operations. In this study, I drop the project management operation because, as the label indicates it, engineering corresponds to operations of supervision for the project to occur and does not directly involve changes in the neighborhood outlook. I rather focus on operations that affect the housing stock such as demolition, production and rehabilitation of social housing. Similarly, the PNRU policy aims at promoting social diversity. Through operations like residentialisation or public facilities provision, one might expect treated neighborhoods to be safer (i.e., through residentialisation operations such as installing a door with a digital code) or to attract more educated residents with new schools or libraries. In general, treated units have undergone several types of operations (half of the neighborhoods have witnessed six operations and more. The multiplication of distinct operation types favors chances of observing significant changes, might it be visual changes or social composition changes.

Each type of operations represents a different percentage of the overall ANRU activity: 9.5 percent of the operations are demolitions, reconstruction represents 29.6 percent of the activity, change of use and requalification both represent less than 1 percent, rehabilitation corresponds to 11.1 percent, residential development 9.5 percent, improving quality of service 3.5 percent, urban planning of the neighborhood 22.2 percent, provision of equipment 9.8 percent, commercial space 1.5 percent, and private housing 1.5 percent. Besides, the frequency of each type of operations highly varies across neighborhoods. Aggregating all operations, I find that more than 8 treated neighborhoods out of 10 witnessed operations of demolition or construction and among them 9 out of 10 witnessed both operations. 3 out of 4 neighborhoods have witnessed rehabilitation or residentialisation operations. 90 percent of the treated neighborhoods were modified through urban planning operations and slightly more than 80 percent saw the production or enhancement of public facilities. Given these figures I have decided to focus on the six types of operations with the greatest occurrence.



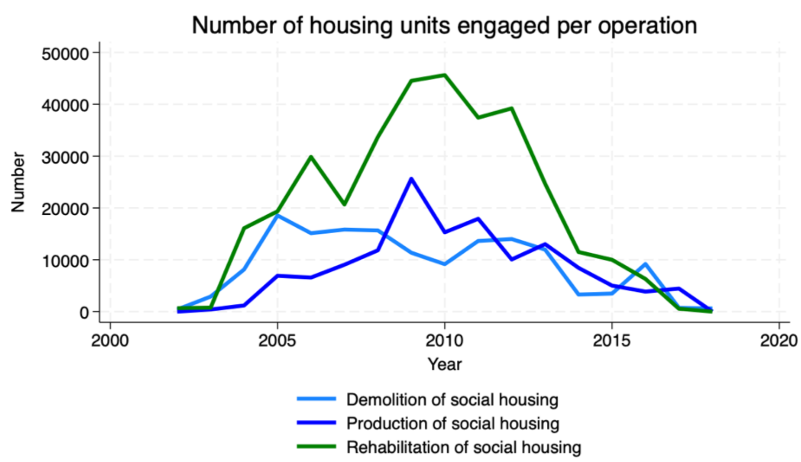

Legend: 01 Demolition of social housing, 02 Production of social housing / Construction, 03 Change of use of social housing, 04 Requalification of degraded old urban blocks, 05 Rehabilitation of social housing, 06 Residentialization of social housing, 07 Improvement of service quality in social housing, 08 Urban Planning, 09 Public facilities, 10 Commercial or artisanal spaces, 11 Intervention on private housing.

Graph 0.2. Proportion of neighborhoods per type of operations

The number of housing units engaged for demolition, reconstitution and rehabilitation significantly increase from 2003 to 2010 and then decrease until 2019. There are more housing units that were engaged at the beginning of the program. Demolition started on average earlier (half of the demolition happened before 2009) to then allow more reconstitution operations to occur (half of the reconstruction occurred after 2010). The proportion of demolished and rebuilt housing on-site highly differ across treated units. Half of the treated neighborhoods which undergone demolition have seen less than 13 percent of their housing stock demolished while a quarter of them witnessed more than 36 percent of demolition. Regarding the production of social housing on-site, a quarter of neighborhoods have had more than 27 percent of their social housing stock rebuilt. There is also a strong positive correlation between neighborhoods with a high demolition and reconstitution rates: 122 neighborhoods belong to the top third of new-builds and the top third of demolitions.


Graph 0.3. Distribution of the proportion of demolished and reconstituted housing units

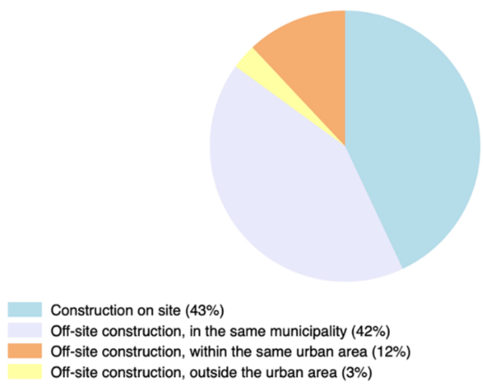
The volume of housing units engaged for rehabilitation is twice bigger than for demolition and reconstitution with a maximum of 45,638 housing units rehabilitated in 2010 and an average of 20,053 per year against 9,058 housing units demolished on average every year and 8,212 rebuilt. In total, 153,990 housing units were demolished and 139,618 rebuilt in metropolitan France.[12] The 2023 ANRU quantitative report indicates a total of 160,000 demolitions and 140,000 reconstructions in metropolitan France and its overseas territories. The underestimation may be attributed to the omission of operations conducted overseas and to the fact that I focus on operations that were delivered in 2019.

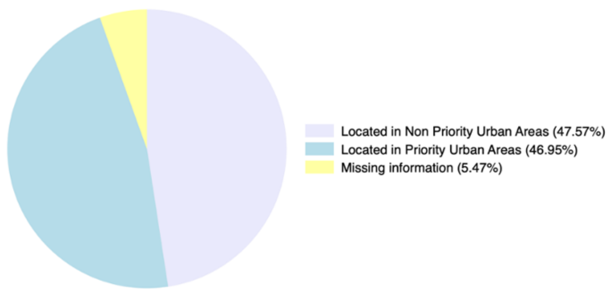



Graph 0.4. Evolution of the number of housing units engaged per operation.

[12] In addition, I estimate the number of rehabilitated housing units at 332,773 and 326,557 residentialized.

In both scenarios however, the level of reconstituted housing is below the demolition rate indicating that the “1 for 1” rule (one housing unit rebuilt for one housing unit demolished) is not respected. Over time, this objective has proven to be unsuitable for certain territories. The ANRU has therefore agreed to adapt the reconstruction rules based on the expressed housing needs in these areas. Besides, the same “1 for 1” rule implied that for 100 housing units demolished 50 had to be reconstituted on site and 50 elsewhere. The reconstruction of the housing supply, partly carried out on-site, reflects a balance between two objectives: maintaining low-rent housing for the needs of the neighborhood's residents and deconcentrating social housing. In the quantitative assessment conducted by the ANRU, it is stated that 57.4% of the housing units had been reconstructed in a ZUS neighborhood; I estimate this figure to be 46.95%.[13]




Graph 0.5. Location of the reconstituted social housing supply

## Budget

ANRU states that it has allocated a total budget of €11.633 billion to the PNRU. I find a total budget of €9.839 billion. This difference is partially explained by the fact that ANRU has allocated around €300 million to the French overseas territories and that engineering operations account for 464 million of the 11.633 billion euros. There is still a difference of around 1 billion to explain. I explain it by the fact that I select operations that were delivered in 2019. This selection choice results in the delete of operations that were budgeted by the ANRU in their report. Besides I select 2020 budget variables as I assumed that ANRU had a better overview of the operations status that in 2018. To check the robustness of the budget variables as well as number of housing units per neighborhood, I compute the average cost of demolition per housing unit. The average cost of a demolished housing is 15,033 euros using our data against 15,069 according to the ANRU. Similarly, constructing a building represents a budget of 16.345 euros per building against 16,696 euros for the ANRU. Finally, while the

[13] The difference is explained by the difference size of the studied sample as I dropped operations that were not finished by the end of 2019. The missing data (5,47 percent) could further explain the difference.

average cost for rehabilitating a building approximates 3,177 euros for ANRU while I find a budget equal to 3,375 euros. The order of magnitude is the same, which gives me confidence in the calculation of the intensity measurements I carry out for the heterogeneity subgroups. Note that the budget variables I am discussing solely represent ANRU subsidies. They do not encompass the entire sum of funds allocated per neighborhood (i.e., ANRU subsidies represent on average only 12,2 percent of the budget allocated for reconstituting housing units). While my focus remains on ANRU subsidies, I acknowledge the potential for improving the measurement of intensity by considering the total funding raised.

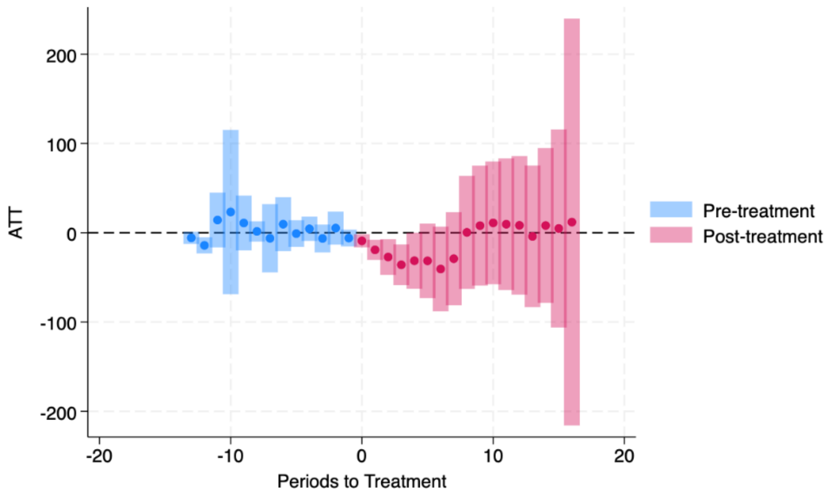
# Results: Global Treatment Effects

This part aims at understanding the causal impact of the PNRU law on income distribution within neighborhoods. For such a purpose, it first examines the impact on the number of households and then turns to inequality indexes. To have a better grasp of the income dynamics within neighborhoods, I then utilize the median, first and last deciles of income per consumption unit. Using the standard TWFE method, I start with 2003 as the treatment date (year at which the law is adopted) and then use the year at which a neighborhood has witnessed its first operation as the date of treatment. I believe that this second definition is more accurate as it takes into consideration the staggered nature of the treatment. However, it may happen that the first work does not actually correspond to the period at which the neighborhood is truly treated. Let's for instance think of neighborhoods which repaint the facades of some buildings in 2004, but witness demolitions later one. In that case, I consider 2004 as the treatment date even if it does not truly capture the core moment of the treatment. Nonetheless, the ANRU prioritized major operations (e.g., demolitions) at the beginning of the program where half of the demolitions took place before 2009. Therefore, I am confident that the year of the first operations conducted in the neighborhood is a relevant treatment date. I employ two econometric methods: a standard regression with fixed effects at the neighborhood level and time-fixed effects. I then utilize the Callaway and Sant Anna estimator (CSDID) for robustness checks.

## Impact of the PNRU law on the number of households

One must first note that the operations undertaken under the PNRU program have caused unusual changes in the number of households within the renovated neighborhoods. Demolitions have indeed prompted residents to vacate their dwellings. Rehabilitation operations, at times, have also necessitated the temporary departure of residents. As a direct consequence to these operations, I expect to observe a decline in the number of households in the short run. The long-term impact will tell whether the PNRU has attracted more households, which seems counterintuitive to fight spatial concentration of income, or whether the number of households remains stable but with a change in the population composition. For the latter scenario, I will regress on additional income variables.

Using 2003 or the year of the first operation within a neighborhood as the treatment date, I find no significant effect on the number of households in renovated neighborhoods (refer to Table 1.1 and Table 1.2 in Annex). The analysis then employs the CSDID estimator to account for the time variation in the treatment date. As expected, findings indicate a significant decrease in the number of households following the policy implementation from time period t+1 to t+3, period during which operations have been the most intensive. Subsequently, although not statistically significant, the number of households appears to stabilize between t+3 and t+7, before exhibiting an upward trend to return to pre-treatment levels. I therefore conclude that the temporary decline in the number of households results in the departure of residents directly caused by operations. Pre-treatment trends are not statistically different from zero, suggesting the presence of parallel trends.




Graph 1.1 Causal impact of the PNRU law on the number of households (CSDID estimator)

A comprehensive review of the literature enriches comprehension of the PNRU law's impact on neighborhood attractiveness. Guyon sheds light on a notable disparity in vacancy rates between treated neighborhoods and the control group, with a difference of 3 percentage points observed in 2003 (Guyon, 2016). Exploring this phenomenon, she presents two distinct assumptions: firstly, attributing vacancy to dwellings slated for demolition, especially as her analysis extends to 2013. Secondly, she posits that this discrepancy could stem from avoidance behavior, with residents possibly shying away from renovated neighborhoods, which, on average, exhibit a poorer socioeconomic profile compared to the control group. Moreover, Chareyron underscores that the PNRU program did not yield a significant uptick in housing values within treated neighborhoods (Chareyron et al.,2020).

## Impact of the PNRU law on income distribution

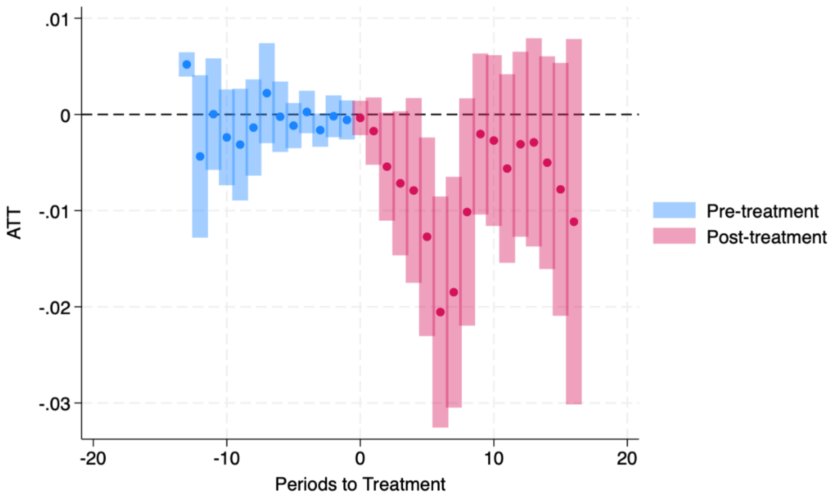
Another objective of the PNRU policy is to promote social mix through the reduction of inequalities between places and populations. I focus in this study on income inequality within treated neighborhoods and rely on the most used inequality index, the Gini coefficient. It quantifies the extent to which the distribution of income among households (more precisely unit of consumption) deviates from a perfectly equal distribution. The closer the coefficient is to 1 the more inequal is the unit of interest. In our case study a coefficient equal to 0 would mean that all the residents of a same neighborhood possess all the exact same revenue. This situation is not necessarily desirable as it depends on the level of the revenue residents possess compared to the city level. A Gini coefficient equal to zero can depict a situation of a spatially concentrated low-income households within a neighborhood. To appreciate such a situation, I need to complement the analysis on income inequalities using the inter-decile ratio and ultimately use income variables (d1, q2 and d9) to have a better understanding of the impact of the PNRU on income dispersion.

### Gini coefficient

Within treated neighborhoods and over the post-treatment period, I find a constant equal to .367 taking 2003 as the treatment date, and to .365 when considering treatment as the year of the first operation in the neighborhood. For comparison purposes, on the scale of metropolitan France, the national mean of the Gini index was .283 in 2004 and .302 in 2012.[14]

Using 2003 as the treatment date, I find a small though significant decrease equal to -.007 (at 99% confidence interval) in the Gini coefficient as a result of the policy, all else equal. Using the year of the first work as the treatment date, the Gini index goes in the same direction with a decrease approximating -.005 (at 95% confidence interval) (refer to Table 1.1 and Table 1.2 in Annex). Results using the CSDID estimator corroborates the previous results. The decrease in the post period is also equal to -.007 on average (at 99% confidence interval) and reaches -.02 at t+6 refer to Table 1.4 in Annex). The decline however does not last with values approaching zero in the long term. Therefore, most of the changes in the Gini coefficient is caused by the departure of the initial population due operations in their households. Having a look at the long-lasting effect is however of paramount importance to interpret the evolution of inequalities within renovated neighborhoods.

[14] Consult: https://www.insee.fr/fr/statistiques/4238393?sommaire=4238781#:~:text=%C3%80%20l'autre%20bout%20de,somme%20des%20niveaux%20de%20vie.




Graph 1.2. Causal impact of the PNRU on the Gini index (CSDID estimator)

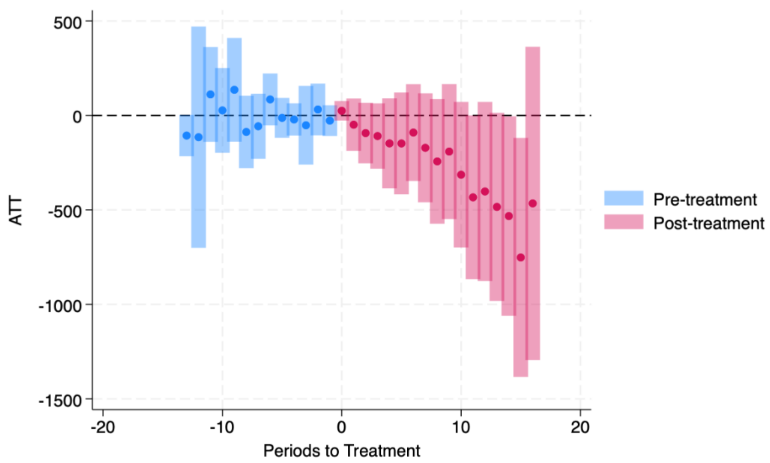
Using both methods, one can assert that income inequality has slightly decreased in the short run, as a result of the policy implementation. However, one cannot state that the policy has resulted in a better income distribution. Such a statement would be inappropriate as the decline in the Gini coefficient can be explained by many mechanisms. Imagine a neighborhood with half of the population who is rich and half poor. Rich people can leave the neighborhoods and be replaced with poorer households, leading ultimately to a decrease in the Gini coefficient but a greater income segregation within renovated neighborhoods. Another possibility is that poor people come out the neighborhood and are replaced by rich households, ultimately leading to gentrification. It can also be an in-between situation with dynamics in both groups that will ultimately lead to the concentration of income. This latter case can be measured using the inter decile ratio. All in all, one must bear in mind that a reduction in the Gini index does not necessarily translate an improved situation within neighborhoods and a complementary analysis on income distribution within neighborhoods must be conducted. A neighborhood where all residents have equal income levels may initially seem positive in terms of equality. However, if the income level is significantly below the city average, it indicates a situation of concentrated low-income, which reflects a less favorable socioeconomic condition.

**Inter-decile Ratio**

The inter decile ratio, equal to D9/D1, is a simple manner to measure and interpret income inequality between the richest 10 percent and the poorest 10 percent. This ratio indicates the evolution in terms of income inequality between the two extremes deciles. However, it does not tell anything about the dispersion of income between the two. Thus, two inter-decile ratios could have the same value despite representing very distinct realities. Bearing its limits in mind, I use the inter-decile ratio as a complementary measure of the Gini index. Using the TWFE regression with either a treatment date set in 2003 or using the year of the first work, I find no significant effect of the law on the inter-decile ratio. The Callaway Sant Anna estimator is also not very conclusive regarding the causal impact of the PNRU law on the inter-decile ratio (refer to Table 1.4. in Annex). All else being equal, I observe that in the absence of the PNRU law, the income of the top 10 percent is, on average, 14.8 to 15.4 percent higher than that of the bottom 10 percent (refer to Table 1.1 and Table 1.2 in Annex). Utilizing INSEE data at the national level spanning from 1996 to 2017, the inter-decile ratio fluctuates between 3.3 and 3.5 percent in metropolitan France.[15] Comparatively, the inter-decile ratio in ZUS is five times greater than at the national level. The discovery of a wider income disparity between the poorest and wealthiest residents within these neighborhoods may not be intuitive, as one might have expected strong spatial segregation with predominantly low-income households and few affluent ones, suggesting a low inter-decile ratio. In the absence of conclusive remarks regarding the inter-decile ratio and in order to interpret the decline in the Gini coefficient, I take a look at the evolution of the median income per consumption unit as well as the first and last deciles income per consumption unit.

**Median income per consumption unit**

Using 2003 at the treatment date, I find a significant decrease on the median income per consumption unit induced by the PNRU. The coefficient of interest is equal to -213 euros at a 90% confidence interval. However, using the second specification I find no significant effect (refer to Table 1.1 and Table 1.2 in Annex). The staggered approach indicates that within treated neighborhoods, median income has seemingly decreased subsequent to policy enactment. On average, the decline in median income equals 224 euros in the post-treatment period (at 90% confidence interval). This observation undermines the belief that the reduction in the Gini coefficient stems from the influx of affluent residents (refer to Table 1.4 in Annex). Had affluent individuals replaced lower-income residents, the median income would have ostensibly risen. Ultimately, this decline seems to be persistent. However, it is possible that the share of medium-income households has increased as found by Guyon and that the decrease in q2 is mainly explained by a large decline in the income of the richest (Guyon, 2016). This is why I also examine the impact of the PNRU law on the last decile.




Graph 1.3. Causal impact of the PNRU on the median income per consumption units (CSDID estimator)

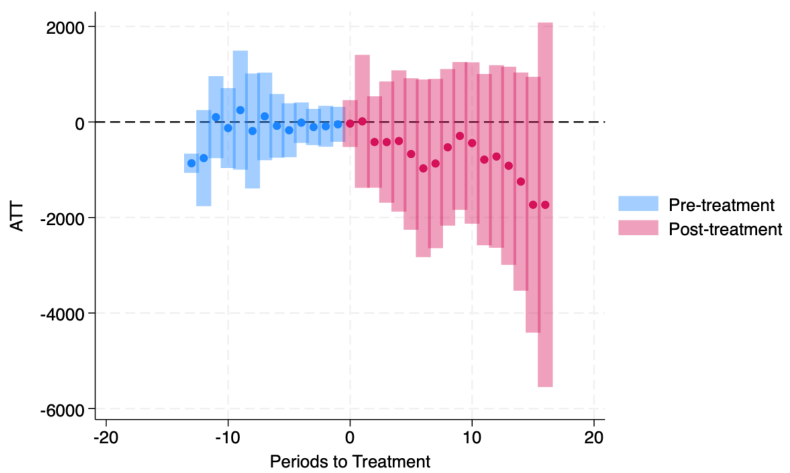
[15] Consult: https://www.insee.fr/fr/statistiques/4238393?sommaire=4238781

**First decile per consumption unit (D1)**

I find no significant effect on the first decile when considering all neighborhoods treated in 2003. However, when redefining the treatment year as the year during which the neighborhood witnesses its first operation, I find a positive significant effect (at 95% interval of confidence) with an estimated coefficient equal to 171 euros (refer to Table 1.2 in Annex). Using the CSDID estimator, I find no significant effect on D1 (refer to Table 1.4 in Annex). The income of the poorest 10 percent of the population has increased as the result of the law. However, as the study is conducted at the neighborhood level, I am not able to tell whether the program improved the living conditions of the same poor residents. However, as shown by Guyon, the PNRU program targeted the housing units of the poorest, resulting in a mechanical departure of these residents (Guyon, 2016). The decline in D1 would therefore translate a situation where the poor left, automatically raising the level of the lowest decile.

**Last decile per consumption unit (D9)**

Using the year of policy implementation as the treatment date, I observe a significant decline in the last decile (at a 99% confidence interval), amounting to a decrease of 697 euros from a baseline of 24,934 euros (refer to Table 1.1 in Annex). I however find no significant effect once the treatment date is defined as the year of the first operation within the neighborhood. The CSDID estimator corroborates previous results with a lasting decline in D9. All else equal, on average in the post treatment period, the estimator indicates an average treatment effect on the treated equal to -593.89 over the studied period (at a 99% confidence interval). I therefore conclude that the PNRU program has provoked the departure of the richest, probably disturbed by the operation works. Nevertheless, when weighting, I have distributed the rich and poor households in the same way. Yet, in the part of the IRIS that intersects with the renovated neighborhoods, there is chance that the proportion of poor households is greater than the share of rich households. In short, I am may be overestimating the proportion of rich people leaving the neighborhood.




Graph 1.4. Causal impact of the PNRU on the last decile (d9) (CSDID estimator)

## Conclusive Remarks

As a result of the PNRU, I find a small decline in income inequality regressing on the Gini index within treated neighborhoods. Regressing on the first decile, I find a significant increase in the income of the poorest 10 percent in the post-treatment period. These results corroborate France Stratégie's note which mentions a 5-point reduction in the proportion of the poorest households (France Stratégie and Guyon, 2024). Similarly, Guyon indicates an average decrease of 2 percentage points in the proportion of households in the first income quartile in all treated neighborhoods (Guyon, 2016). Besides, her research suggests that occupants of renovated housing were generally more affluent than those residing in social housing in 2003. Therefore, I assume that the increase in the lowest decile is not solely caused by the temporary departure of the poorest targeted by the program, but it also translates a situation where richer residents, though still relatively poor, settle in the neighborhood after the demolitions. Concurrently, this analysis reveals a decrease in the income of the wealthiest 10 percent following the implementation of the PNRU law. From this, I infer that the PNRU law has contributed to a reduction in income dispersion within the treated neighborhoods, driven by a reduction in the two extremes of the income distribution. It is worth noting that the decline in income inequality is temporary in nature, largely stemming from the transient departure of households during extensive renewal urban efforts. Ultimately, the concentration of income values is driven towards low deciles levels, suggesting an impoverishment of the neighborhood as a result of the PNRU.

Guyon finds that the PNRU has caused a significant increase in the level of poverty in the private housing stock renovated neighborhoods, and a twofold decrease in the level of poverty in the social housing stock (Guyon, 2016). The improvement in the poverty level is mainly driven by the decrease in the proportion of households belonging to the first decile (defined at the national level) within renovated neighborhoods, and with an increase in the proportion of households belonging to the second and third quartiles. Her findings align with the idea of a reduction in the income dispersion within renovated neighborhoods. In addition to the distinction made between the social and the private housing stocks, she provides a more nuanced understanding by conducting an analysis based on the type of dwelling inhabited by households—whether destroyed, constructed, or stable between 2003 and 2013. This refined approach at the housing unit level sheds light on income trends within renovated neighborhoods. Specifically, while median income and third quartile income proportions slightly decrease in housing units that remain intact over the studied period (by -1,7 percentage point for q2 and by -2 percentage points for q3), these same variables witness significant increases in housing units that have undergone demolition during the same period (by +7,7 percentage points for q2 and by +6,9 percentage points for q3).

Regarding the first decile, my results seem to align with Guyon's findings: there are fewer extremely poor households in the renovated neighborhoods. However, as stated by Guyon, this decline is mostly driven by the temporary mechanical effect of demolition, which targeted housing where the population was the poorest (Guyon, 2016).

At this stage, I assume that treated neighborhoods are poorer on average as a result of the PNRU as the median income decreases. I indeed find that at the neighborhood level, the median income per consumption unit decreases, as does the income of households belonging to the ninth decile. These findings seem at first glance to contradict the increase indicated by Guyon in the proportion of households belonging to the second quartile (and reinforced by a comparable increase in the third quartile) (Guyon, 2016). However, I am not conducting a direct comparison of identical variables. Guyon mentions proportions of households belonging to the second and third quartiles, compared to the national level. In my case, I interpret levels of income at the neighborhood level. It is entirely possible that the proportion of households belonging to the second quartile defined at the national level increases within treated neighborhoods while the median level of income located within the same neighborhood decreases.

Finally, this study surpasses the scope of 2013, paving the way for potential new effects and interpretations over the long term. For example, the observation of a decline in d9 in my findings, while Guyon reports no significant impact on the proportion of households in the fourth quartile,[16] might suggest that the wealthiest residents were ultimately affected by the renovations and consequently relocated from the neighborhood, an outcome that was not necessarily evident in 2013 (Guyon, 2016).

## Heterogeneity (1)

Taking advantage of the large scale of this urban renewal program I create in this section groups to control for potential hidden heterogeneous effects in the treatment. In this first heterogeneity section, I attempt to create groups based on my knowledge of the PNRU program. I thus select the three main types of operations: demolition, production, and rehabilitation of social housing. I constitute a first group made up of neighborhoods belonging to the top third of the most demolished and the top third of the most rebuilt neighborhoods (N=122). I built upon Guyon and France Stratégie's note which both attach particular importance to the level of demolition in the impact of the law on income distribution (Guyon, 2016 ; France Stratégie and Guyon, 2024). Besides, I wanted to add other dimensions that could have influenced the treatment effect. As over 9 neighborhoods out of 10 undergo rehabilitation to varying intensities, I also incorporate this operation. Nonetheless, since the majority of neighborhoods experience rehabilitation coupled with demolition and construction, any potential heterogeneity effects would likely stem from these latter two operations. Constituting a subgroup with only rehabilitated neighborhoods (N=22) would lack statistical power. I thus

[16] Note that in Guyon (2016) the share of households belonging to the fourth quartile is equal to 10.1%, making it a comparable measure to the last decile (10%).

create a housing-intensive group by selecting the two-thirds of the most rehabilitated neighborhoods that belong to the first sub-group to get a housing-intensive subgroup. Ultimately, I create a third and last group that have been intensively demolished but have undergone little on-site reconstruction. As only 14 of the renovated neighborhoods were intensively demolished (last third) and very little rebuilt (first third), I have included neighborhoods with more dispersed intensity values (refer to Table 2.1).

The intensity of these operations significantly varies among neighborhoods. To address this variation, I compute the ratio of the number of housing units engaged out of the total number of housing units in the neighborhood in 2003.[17] I chose 2003 to ensure that it represents the number of housing units before any changes that can be attributed to the PNRU law. There are some inconsistencies, although marginal, especially when the number of housing units committed per operation exceeds the total number of housing units in the neighborhood. Besides, it happens that the number of housing units within a neighborhood is surprisingly low (below 50 for seven neighborhoods). In this case, I drop them for the measure of intensity because they could bias my estimates. These misestimations are explained because housing units are defined at the cadastral section unit where homogeneous distribution of housing units is assumed. It has however been shown that the housing density is higher in the part of the cadastral sections that covers the studied neighborhoods, arguing in favor of underestimation in the total number of housings per neighborhood.[18] Additionally the delimitation of some neighborhoods might evolve over time and might be different than the year 2003 definition. One way to improve the ratios would be to define the denominator according to the year the operation took place.

| | | **On-site construction intensity** | | | Total |
|---|---|---|---|---|---|
| | | Low | Medium | High | |
| **Demolition intensity** | Low | 102 | 32 | 13 | 147 |
| | Medium | 44 | 98 | 24 | 166 |
| | High | 14 | 31 | 122 | 167 |
| Total | | 160 | 161 | 151 | 480 |

Footnote: In pink, Neighborhoods that have witnessed heavy demolitions but low on-site construction. In blue, Neighborhoods that have witnessed heavy demolitions and on-site constructions. Among these 122 neighborhoods, 92 have witnessed heavy rehabilitation operations and thus belong to the housing-intensive subgroup. Besides, the total number of neighborhoods should be equal to 533 and not 480 (loss of 53 neighborhoods that did appear in the Filocom database in 2003, preventing the calculation of the proportion of committed housing).

Table 2.1. Share of neighborhoods per intensity in terms of demolition and construction

The purpose of this section is to assess whether the effect of a high-intensity operation has a different impact on outcomes of interest. However, I realized how challenging it is to maintain a consistent level of intensity while varying another aspect for a different type of operation. For instance, it is not possible to create a group with neighborhoods that are highly demolished and very minimally reconstructed on-site because such neighborhoods do not exist. In reality,

[17] The total number of housing units is computed using the Filocom 2003 database.
[18] France Stratégie and Guyon (2024) and Guyon (2016).

the highly demolished with low reconstruction rate group resembles a "less renovated" group because highly demolished neighborhoods are also extensively reconstructed (refer to Table 2.2). As there is both a relatively lower demolition and reconstruction rates, results are more difficult to interpret. In the results part, I will therefore interpret the outcomes for the initially highly demolished with low reconstruction rate group as the impact of the PNRU within relatively less renovated neighborhoods.

| Groups | Characteristics | Average demol | Average constr | Average rehab | Number of neighborhoods |
|---|---|---|---|---|---|
| Demolition and construction intensive | The top third of neighborhoods that have undergone intensive demolitions (> 24%) and the top third of neighborhoods that undergone constructions on-site (> 11%) | 62,31% | 33,94% | 43,57% | 122 |
| Housing intensive | Neighborhoods in the first group, which also experienced rehabilitation of over 12%. | 56,85% | 29,34% | 57,49% | 92 |
| Relatively intensive demolition and low construction on site or Relatively low intensity | Refer to Table 2.1. | 29,30% | 3,31% | 42,42% | 89 |

Table 2.2. Subgroups based on different intensity in the treatment

## Results

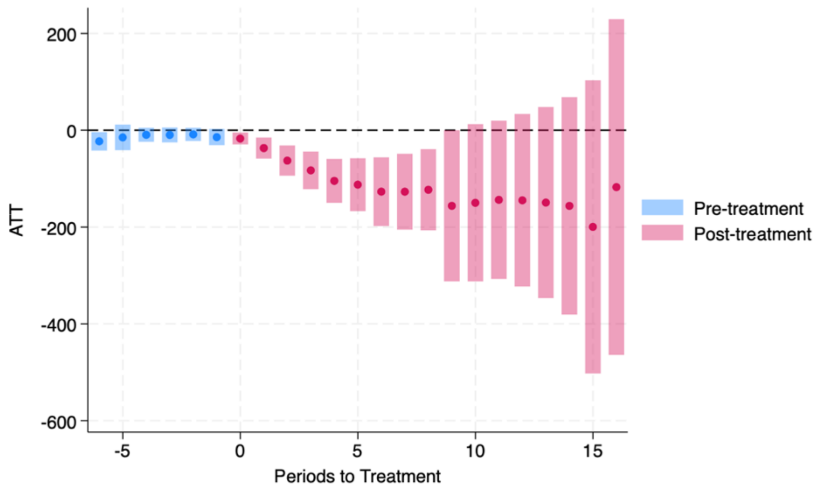
In this section, I delve into the results obtained in the initial part and juxtapose them with those from analyses controlling for heterogeneity in the treatment. Ideally, I aim to pinpoint the specific types of operations that exert the most significant influence on the variables of interest. This endeavor would facilitate advising policymakers on the contexts in which the law proves most efficacious. To this end, I use the same estimation strategy as in the first part. Both estimators demonstrate comparable effects, bolstering confidence in their reliability. I only use the year of first work as the treatment date for the TWFE regression. Finally, I compare intensively treated neighborhoods with the same control group (N=410) as in the first part.[19]

**Impact of the PNRU law on the number of households**

While I find no significant effect of the PNRU law on the number of households in the global treatment effect part, the subgroups reveal a significant decline at 99% confidence interval, using both econometric methods. The magnitude of the decline is more pronounced in the housing-intensive subgroup with a coefficient approximating -114 to -130 households on average over the post-treatment period (refer to Table 2.3 and Table 2.9 in Annex). The CSDID estimator even reveals the existence of an anticipation effect with on average a decrease equal

[19] I drop treated units that do not belong to the subgroup. The number of dropped neighborhoods change for each subgroup.

to -13 (and -9 for the demolition and construction intensive subgroup) households in the pre-treatment period at 99% confidence interval. To some extent, households left the renovated neighborhoods before the treatment actually took place. While I initially noted a mechanical decrease in the number of households resulting from the operations, I discover in this section that the departure is persistent. To reach its objective fighting spatial income segregation, the PNRU has reconstructed outside the treated neighborhoods which can explain the persistent drop. Targeting the housing units of the poorest households and reconstructing social housing outside the deprived neighborhood might have helped them to relocate within more socially diverse areas. However, my inability to track residents over time precludes determining whether, as a result of the PNRU, they transitioned to places that has enhanced their life prospects.




Note: the standard errors increased over time as the sample size decreased.

Graph 2.1. Impact of the PNRU on the number of households in the housing-intensive subgroup (CSDID estimator)

## Impact of the PNRU law on income distribution

### Gini coefficient

Without the interaction terms the Gini coefficient decreases by -.007 on average over the post-treatment period using both estimators. I find that the Gini index decreases twice more in housing-intensive neighborhoods (by -.011 with TWFE to -.018 with CSDID at 99% confidence interval), to three times more in heavily demolished and reconstructed on-site neighborhoods (by -.015 with TWFE to -.020 with CSDID at 99% confidence interval). In the relatively low renovated neighborhoods, I find no significant effect of the PNRU on income inequality. I conclude that a higher number of demolitions has resulted in a stronger reduction in income inequality as a result of the law.

**Inter-decile ratio**

While I found no significant effect in the global part, I observe significant changes in the inter-decile ratio controlling for heterogeneity in the treatment effect. The main driver for a reduction in the inter-decile ratio is when demolition and construction on-site are intensive. The TWFE regression shows that, as a result of the PNRU, the difference in income dispersion between the 10 percent wealthiest and the 10 percent poorest has declined by 2.7 percentage in the first subgroup, resulting in a smaller income distribution within neighborhoods (refer to Table 2.5).

**Median income per consumption unit**

Regressing on the median income, I find no effect within highly demolished and reconstructed on-site neighborhoods, with coefficients that are not significant and go on opposite directions using the two estimators. The median income seems to decline in the housing intensive subgroup, though not significantly. I therefore presume that the observed decline in median income found in the global treatment effect part is mostly driven by neighborhoods that have undergone little renovation. I notably find a significant decline equal to 543 euros (at 99% confidence interval) in relatively little renovated neighborhoods (refer to Table 2.9) using the CSDID estimator.

**First decile per consumption unit (D1)**

I find that the first decile income increases in neighborhoods heavily demolished and reconstructed on-site (by 241 euros at a 95% confidence interval with the CSDID estimator, refer to Table 2.9 in Annex), as well as in the housing-intensive subgroup, though not significantly. Again, demolitions have provoked the departure of the poorest households. However, within low-renovated neighborhoods, the same dependent variable decreases (by 242 euros using the TWFE regressor at a 95% confidence interval, refer to Table 2.6). As this group differs from others on multiple aspects, it is challenging to interpret such a decline. Such a decline can either be interpreted by the fewer demolitions that imply fewer very poor departures, or the absence of a housing supply resulting from a very low construction rate prevents richer households from moving in in the medium to long term.

**Last decile per consumption unit (D9)**

The analysis reveals a significant decrease in the global effect of the treatment when considering the entire sample. Controlling for heterogeneity in the treatment, the income of the last decile also decreases in the three subgroups, though at different intensity. As a reminder, the decrease observed in D9 is determined by the disparity between its levels before and after the treatment, contrasted with the hypothetical level D9 would have attained in the absence of the program. In the highly demolished and reconstructed neighborhoods, d9 decreases not significantly by 229 to 693 euros depending on the estimator (refer to Table 2.7 and Table 2.9 in Annex). In the housing-intensive neighborhoods, the decline is more pronounced ranking from 465 to 802 euros. The decline is however significant (at 99% confidence interval) and consequent in relatively less renovated neighborhoods with a decline estimated between 1012 euros to 1338 euros. Again, such a decrease is hard to interpret, either the richest households left because they were disturbed with the on-site work or the absence of a housing supply due to a low reconstruction rate has left the neighborhoods in a more deprived socioeconomic situation with less opportunities for middle class residents to settle in.

## Conclusive remarks

Controlling for heterogeneity in the treatment through the main operation types, I gain a better understanding of the underlying trends behind the apparent decrease in income dispersion within renovated neighborhoods. Similar to Guyon and France Stratégie's note[20], I attribute particular importance to the intensity of demolition that emerges as a key determinant to reduce income dispersion within renovated neighborhoods (Guyon, 2016 , France Stratégie and Guyon, 2024). In the third most demolished neighborhoods, the Gini index decreases three times more and persistently compared to the global treatment effect.

In highly demolished and reconstructed neighborhoods, the decrease in income dispersion is explained by the tightening of earnings around more central values. Demolition led to the temporary departure of the poorest households whom housing were the most targeted by the program implying an increase in the income of the first decile. On the other side of the distribution, the wealthiest households have left the neighborhoods, probably due to disruptive works implied by demolition and reconstruction. I find that the income gap between the richest and the poorest households has decreased by 2.7 percent on average as a result of the PNRU law. Building upon Chareyron and al. who observe a shift in housing units from lower-income to higher-income categories (Chareyron et al.,2020), I additionally assume that the high level of reconstruction on-site has allowed new settlers to move in. Presumably more modern and secured, these new housing units attracted wealthier households, though probably still belonging to low deciles as the median income per consumption unit does not increase significantly.

Within less intensively renovated neighborhoods, the richest and the poorest have also left. While the departure of the poorest should have reduced the overall level of poverty at the neighborhood level, the simultaneous drop in the last decile has provoked an overall impoverishment of the neighborhoods. In other words, the "gain" in income caused by the departure of the poorest is outbid by the "loss" in income provoked by the richest who left massively. Therefore, contrary to the heavily reconstructed neighborhoods, incomes did not converge around the pre-treatment median point, but instead fell, causing the neighborhood to become poorer. As this group was initially intended to be made up of neighborhoods that had undergone heavy demolitions and little reconstruction, I need to improve the classification method in order to verify the results obtained.

[20] France Stratégie (2024) and Guyon (2016) both focus on the 25 percent most intensively demolished neighborhoods.

# Heterogeneity (2) Neighborhood Classification

Similar to the first heterogeneity subgroups, the neighborhood classification serves as a method to control for the heterogeneity in the treatment. However, in the previous section, I formed groups based on my knowledge of the program. Here, I adopt a totally agnostic method for the creation of similar groups. This implies that the classification includes almost all types of operations and that one neighborhood can belong to one group only. The classification provides a structured framework to understand the effectiveness of the policy across different types of neighborhoods. It is particularly crucial in the realm of public policies, as it allows for a more targeted assessment of the treatment's impact on neighborhoods truly affected by the policy. By categorizing neighborhoods into distinct groups, each comprising solely renovated neighborhoods, I gain insight into which types of neighborhoods experience the most significant effects from the policy. This approach enhances the precision of my analysis and facilitates a more nuanced understanding of the policy's implications for income distribution. Note that in this section I use year of first work as treatment date for the TWFE regressions.

## The Ward method

In crafting a neighborhood classification, I deploy a hierarchical ascending approach employing the Ward method. To grasp the nuances of this method, it is pivotal to gauge the reliability of the classification itself. Imagine neighborhoods scattered across a multidimensional graph, with each dimension representing a characteristic utilized for classification. The hallmark of a robust classification lies in the proximity of neighborhoods within the same class—they exhibit akin traits, forming clusters in this graph. Conversely, neighborhoods outside the same class diverge significantly, manifesting considerable spatial distance. This reliability can be quantified mathematically through total inertia, the amalgamation of intra-class variability (intra-inertia) and inter-class variability (inter-inertia). A perfect classification, where neighborhoods within the same class are identical, yields a total inertia of 1.

The Ward method attempts to minimize intra-inertia (or to maximize inter-inertia). To do so, I start from a classification where each class is composed of one neighborhood. In this starting step there is therefore no intra-variability and inter-variability is equal to 1. I then aggregate class a and b in a way that minimize inter-inertia such that:

$$Inertia\ (a)\ +\ Inertia\ (b)\ =\ Inertia\ (a\ \cup\ b)\ -\ \frac{N_a * N_b}{N_a + N_b} * d^2(a,b)$$

where $N$ is the number of neighborhoods within a class and $d$ is the Euclidian distance between the centers of gravity of class a and b (again think of a graph). The objective is to minimize $-\frac{N_a * N_b}{N_a + N_b} * d^2(a,b)$. This method groups together classes with very similar centers of gravity.[21] For a visual interpretation of the classification, I present in this paper the dendrogram (Graph 3.1) which displays on the ordinate the dissimilarity index, which in this case corresponds to the Euclidean distance (the most commonly used criterion for continuous variables).

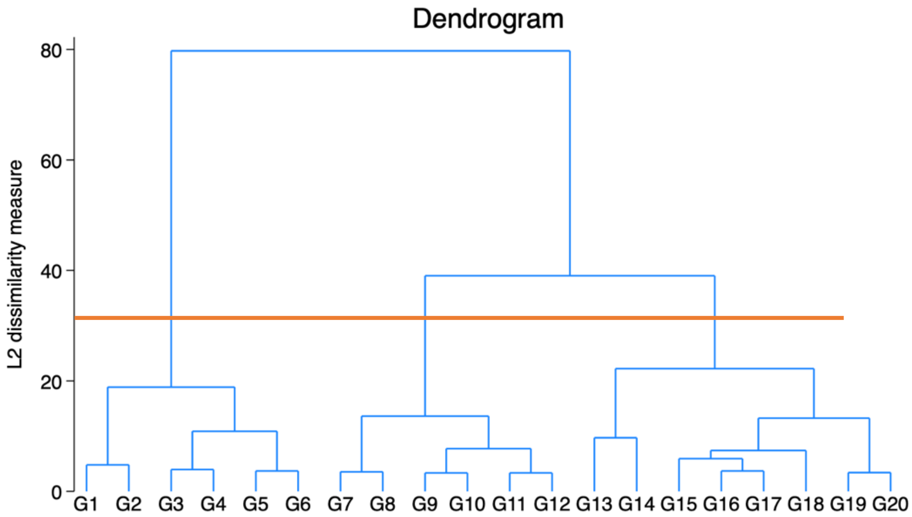
## Classification

I incorporate nearly all types of operations, presenting a holistic view of neighborhood transformation. [22] Among the 529 neighborhoods, 528 are represented in this classification.[23] Each operation serves as a distinctive characteristic. However, before delving into neighborhood categorization, it is imperative to establish a unified metric for measuring the intensity of these operations. My approach involves standardizing intensity measurements across all characteristics, ensuring a consistent evaluation framework. To achieve this, I adopt various metrics tailored to the nature of each operation. For instance, for demolition, reconstruction, rehabilitation, and residentialization efforts, I gauge intensity by calculating the proportion of housing units involved relative to the neighborhood's total housing stock. Similarly, for initiatives aimed at enhancing service quality, I quantify intensity by assessing the budget allocated per housing unit. Urban planning endeavors, including infrastructure improvements and commercial development, are evaluated based on the budget allocated per unit area of the neighborhood. Standardizing these intensity metrics involves normalizing their values to a range between 0 and 1, ensuring comparability across different operations. With these normalized metrics in hand, I employ the Ward method to delineate distinct classes within renovated neighborhoods. The resultant dendrogram provides a visual representation of the hierarchical clustering, elucidating the underlying patterns and relationships among diverse urban areas. The dendrogram analysis indicates a compelling case for dividing the sample into three distinct classes. While alternative choices were feasible, opting for a finer segmentation risk would have allowed the creation of more cohesive groups but at the expense of less statistical. By consolidating into three classes, I preserve the robustness of my analysis while still capturing meaningful variations and patterns within the dataset. This strategic decision maximizes the interpretability and utility of the classification results, empowering policymakers and urban planners with actionable insights for targeted interventions and resource allocation.

[21] On Stata I use the command cluster wardslinkage variables, measure(L2)

[22] I do not consider change of use, requalification, commercial spaces, and intervention on private housing operations; either because their distribution is flat meaning that there is no difference in the intensity or that too few neighborhoods are affected. As a result, when adding these operations, the classification is more or less the same as the one I am using.

[23] One neighborhood has not witnessed any of the selected operations.




Graph 3.1 Dendrogram

In Table 3.1, I present the intensity metrics for each operation across the three distinct groups. Group 1, characterized as the low-intensity group, encompasses 268 neighborhoods. Moving to Group 2, I find neighborhoods predominantly marked by low-intensity operations, with notable exceptions in rehabilitation and residentialization, an average of 56.9 percent of housing units have undergone rehabilitation and 75.6 percent have experienced residentialization. This group comprises 129 neighborhoods. Meanwhile, Group 3 comprises 131 neighborhoods where demolition and construction operations have been notably intensive, with an average of 62.5 percent of housing units demolished and 55.2 percent reconstructed on-site.

| | Proportion of neighborhoods | Demolition | Construction | Rehab | Resid | Services | Planning | Facilities |
|---|---|---|---|---|---|---|---|---|
| Group 1 | .507 | .093 | .089 | 0.196 | .153 | .018 | .051 | .072 |
| Group 2 | .244 | .208 | .133 | 0.569 | .756 | .032 | .085 | .115 |
| Group 3 | .248 | .625 | .552 | 0.420 | .407 | .05 | .142 | .347 |

Footnote: Group 1 low-intensity, Group 2 rehabilitation and residentialization intensive, Group 3 demolition and construction intensive

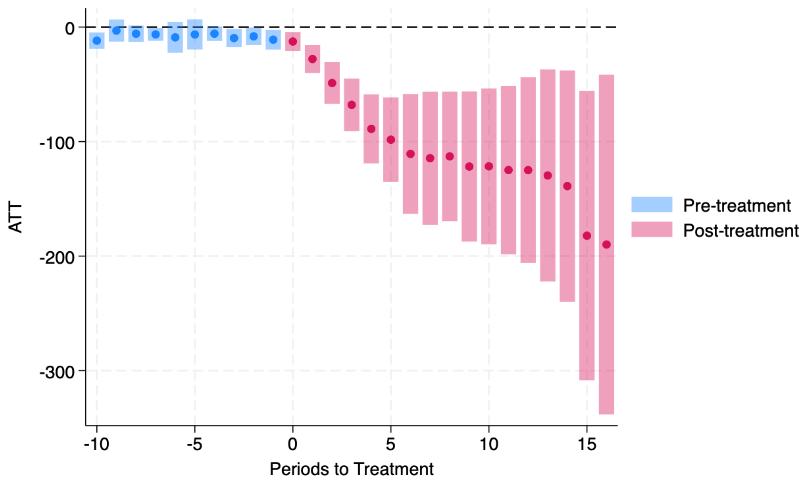
Table 3.1. Presentation of the subgroups

## Results

### Impact of the PNRU law on the number of households

Using the standard TWFE regression, I observe on average over the post-treatment period a decrease in the number of households equal to -84.59 (99% confidence interval) in

Group 3 (refer to Table 3.2 in Annex). Results are not significant in Group 1 where the proportion of demolished housings has been relatively low. These results corroborate the previous ones: the higher the demolition rate, the stronger the decline in the number of households. I additionally learn that rehabilitation has also probably led to departures as I find a decrease in Group 2, though not significant (equal to -30.32). The temporary departure of households as a result of rehabilitation operations is confirmed using the CSDID estimator. In addition, this estimator indicates a persistent decline in the number of households over the studied period.

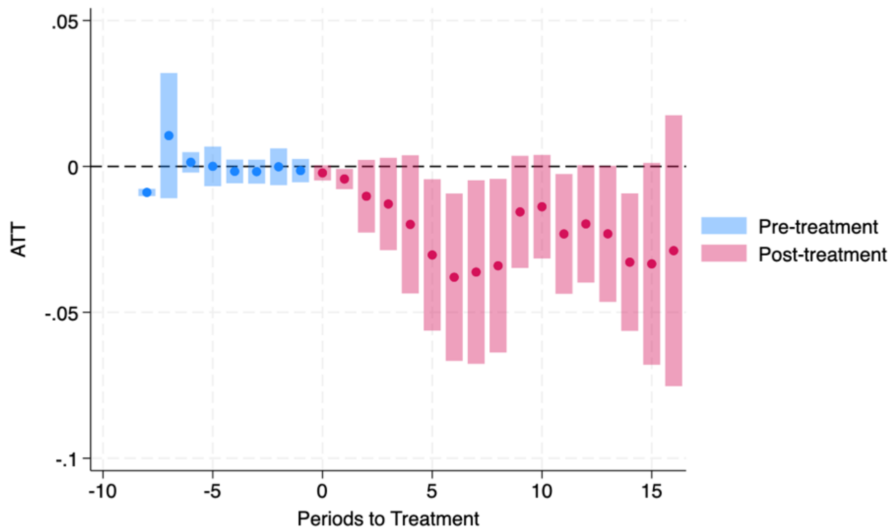



Graph 3.2. Causal impact of the PNRU on the number of households in highly demolished and reconstructed neighborhoods (Group 3) using the classification (CSDID estimator)

**Impact of the PNRU law on income distribution**

**Gini coefficient**

I find a significant decrease in the Gini coefficient in Group 3, approximating -0.020 using both regressions methods at a 99% confidence interval (refer to Table 3.3 and Table 3.8 in Annex). Its magnitude is aligned with previous results: the decrease in the income dispersion within neighborhoods is three times bigger in the short in highly demolished and reconstructed neighborhoods than elsewhere. In Group 2, I observe the same trends, though not in a significant way. In Group 1, I also find a significant decrease in the Gini coefficient equal to -.005 (relatively smaller than the one found in the global treatment effect part). Using results of the Gini coefficient, I can already attest that the changes in income inequality are significant and bigger in highly demolished and rebuilt neighborhoods. However, the sharp decline in the short run must be attributed to the temporary departure of the residents. The long-term effect of the program on income inequality is relatively smaller.



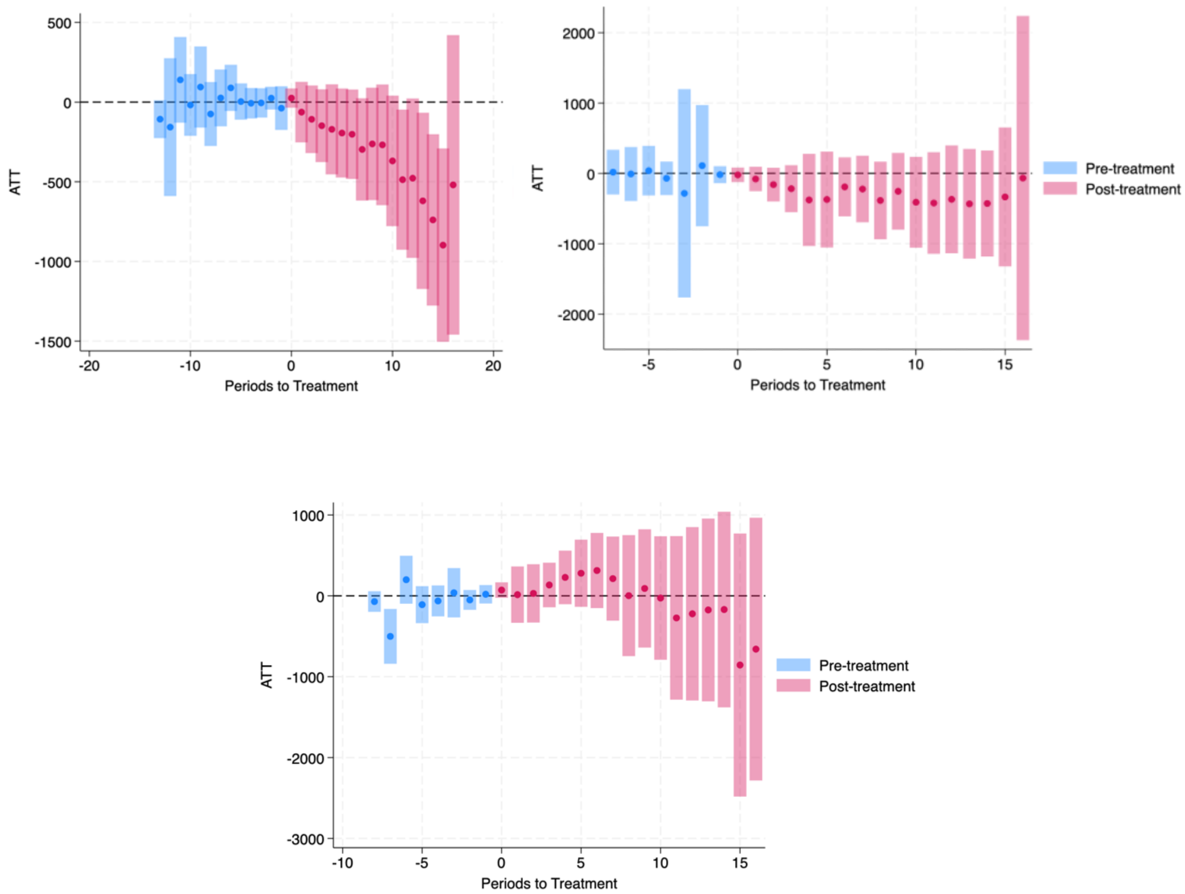

Graph 3.3. Causal impact of the PNRU on the Gini coefficient in highly demolished and reconstructed neighborhoods (Group 3) using the classification (CSDID estimator)

**Inter-decile ratio**

In Group 3, the drop in income inequality within neighborhoods is also observable relying on the inter decile ratio. Using the TWFE regression, the decrease is equal to -.040 (at a 99% confidence interval, refer to Table 3.4 in Annex). With the CSDID estimator, I also find a decrease equal to -.036 (at 95% confidence interval, refer to Table 3.8 in Annex). Surprisingly, I find an increase in the inter decile ratio for Group 1, though not significant. This observation implies that the decline in the Gini index is of different nature in subgroups. For the inter decile ratio (D9/D1) to increase, either D9 increases (which is unlikely based on previous observations) and/or D1 decreases. I therefore anticipate a decline in the first decile. Simultaneously, for the Gini index to decrease, income variables must converge (income dispersion must decrease) either towards central values, or towards one end of the income distribution. With an anticipated decline in d1, I also assume that income values converge towards low deciles, suggesting an impoverishment at the neighborhood level.

**Median income per consumption unit**

The impact of the PNRU on the median income highly differs across groups. The CSDID estimator reveals a persistent decline in the median income in Group 1, with an ATT equal to -288 in Group 1 at a 95% confidence interval. For Group 2, the ATT equal to -283, though not significant (refer to Table 3.8 in Annex). Using the TWFE method, coefficients are also negative though not significant in these two groups. Neighborhoods which did not witness demolitions and reconstructions intensively have seen their median income decline. I find no significant effect on the median income for intensively demolished and reconstructed neighborhoods. Graph 3.4 reveals a tendency towards an increase in the short run that can be attributed to demolitions which mainly affected the poorest households (with a smaller share of poor households within the neighborhood, Q2 increases). As observed in the heterogeneity section, the observed decline in the median income does not seem to be driven by demolition-intensive and construction-intensive neighborhoods.




Footnote: Low intensive group (Group 1 top left), intensive rehabilitated and residentialized neighborhoods (Group 2 top right), and highly demolished and reconstructed neighborhoods (Group 3, bottom) using the classification

Graph 3.4 Causal impacts of the PNRU on the median income per consumption unit using the classification (CSDID estimator)

**First decile per consumption unit**

The impact of the PNRU on the first decile is significant for Group 3 with an increase estimated at 357 euros using the CSDID method and equal to 433 euros using the TWFE method, at a 99% confidence interval in both cases (refer to Table 3.6 and Table 3.8). Group 2 seems to follow the same trends, but coefficients are relatively smaller. For the low intensity group, the effect of the PNRU on the first decile seems to be null to negative as indicated by the CSDID estimator. The impact of the PNRU on the first decile is thus related to demolition intensity: when demolitions occurred, the poorest households had to leave, eventually increasing D1. As a result, the decrease in income inequality is of different nature across each group. Low-intensity neighborhoods seems to be poorer with income values converging towards a lower median point. On the other hand, heavily demolished and to a lesser extent rehabilitated neighborhoods did not witness a significant decrease in the median income explained by an increase in D1. I conclude that only neighborhoods with numerous demolitions and reconstructions on-site have allowed to either improve the living conditions of the poorest or, and more probably, attract richer residents from deciles below D5 as the median income does not increase significantly in these neighborhoods.

**Last decile per consumption unit**

Similar to previous results, for the three groups the level of D9 declines over the studied period. Results using the CSDID estimator shows that the wealthiest households have left neighborhoods that were not intensively treated (Group 1) in a significant way: I observe a decline equal to -658 euros in their income at a 99% confidence interval (refer to Table 3.7 and Table 3.8 in Annex). Contrary to Guyon who finds no significant effect of the PNRU on the proportion of households belonging to Q4 in 2013,[24] I find a decrease in their representativeness within neighborhoods in 2019 (Guyon, 2016). I posit that the wealthiest individuals were notably affected by the operations conducted under the PNRU program and likely departed in a substantial manner, although this might not have been readily observable in 2013. Ultimately, I acknowledge the possibility of overestimating their departure, particularly considering the initial assumption of uniform distribution of poor and wealthy households within an IRIS.

## Conclusive remarks

The development of a neighborhood classification, categorizing renovated neighborhoods into three distinct groups—ranging from low-intensity operations across all types (Group 1), to low-intensity operations but intensive rehabilitation and residentialization (Group 2), to high-intensity demolition and construction (Group 3)—builds upon previous findings. The consistency of results obtained through both the TWFE and CSDID estimators strengthens my conclusions, reinforcing the robustness of the analysis. The PNRU law has caused a reduction in income dispersion in all renovated neighborhoods. However, the underlying mechanisms are of different nature depending on the type and the intensity of the operations neighborhoods were subject to.

Highly demolished and reconstructed neighborhoods echo previously observed dynamics (evidenced by the Gini coefficient and the inter decile ratio). The observed shifts in intra-neighborhood income disparities, spurred by considerable demolitions and on-site reconstructions, can be attributed to already observed phenomena: D1 experiences an increase while D9 registers a decline (albeit not statistically significant). Heavily renovated areas witness a diminished presence of extreme poverty allowed by the massive departure of the poorest households who were replaced by richer, though still relatively poor households as the median does increase in the medium to long term. Income disparities thus constrict around

[24] As households belonging to Q4 is estimated to approximate 10% in Guyon's report (2016), I am comparing the same households when using D9.

middle deciles, presenting fewer instances from the first and ninth deciles at the national average. Consequently, the tightening of incomes around the median keeps the level of poverty relatively comparable to that before the program was introduced.

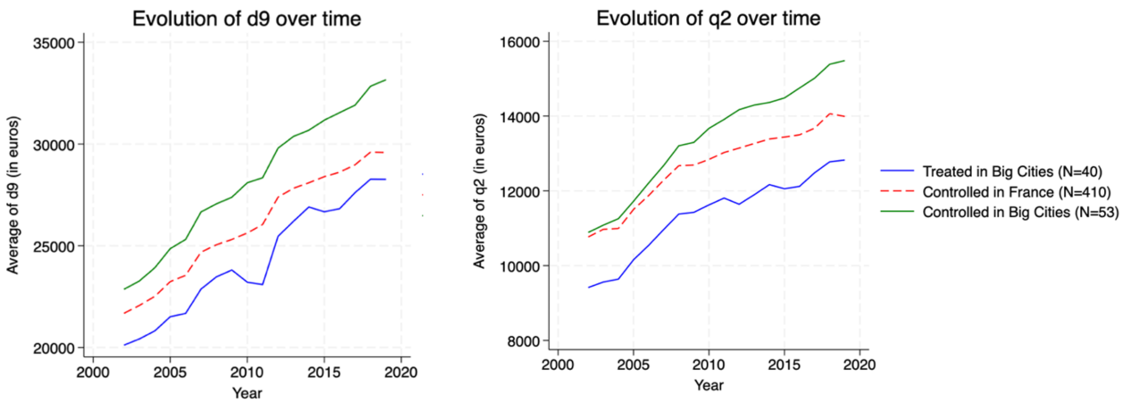
In highly rehabilitated and residentialization neighborhoods, akin trends to group 3 manifest, albeit less prominently and without statistical significance. Despite relatively robust rehabilitation and residentialization efforts within this group, their impact on income inequalities appears subdued. Hence, special emphasis is placed on demolitions and constructions as pivotal measures to curtail intra-neighborhood disparities. Finally, in examining household evolution, I discern that rehabilitation initiatives, akin to demolition, prompt temporary resident displacement.

In contrast, within low intensity neighborhoods, the Gini coefficient appears to decline for distinct reasons. Unlike in other neighborhoods, where income distribution tightens around the median, relatively untouched neighborhoods appear to experience impoverishment. This is evidenced by a noteworthy decline in median income, driven by a substantial exodus from the ninth decile.

## Heterogeneity (3) Location specification

I then assess whether the PNRU program has had a different treatment effect given location characteristics specific to each neighborhood. Intuitively, I assume that deprived neighborhoods located within big cities must have witnessed a significant change in their social composition after being rehabilitated. Indeed, given their attractive location, a program designed to beautify previously deprived and stigmatized neighborhoods must attract wealthier populations in the long term. I therefore expect neighborhoods located in big cities to relatively attract higher incomes compared to other neighborhoods in France that might benefit from a less valuable location. For such an assessment, I select neighborhoods located in the four biggest French cities (Paris, Marseille, Lyon and Toulouse). Furthermore, I exclusively focus on neighborhoods situated within the municipality, excluding those within the agglomeration. This approach ensures that I can observe the impact on neighborhoods located in areas where significant neighborhood renovations could substantially boost the demand for housing supply. On the other hand, given the disruptive nature of the work and the relatively more deteriorated situation in renovated than non-renovated neighborhoods pre-treatment, I expect non-renovated neighborhoods located in big cities to have witnessed a stronger arrival of richer households. All in all, I anticipate that the PNRU program has spurred gentrification more prominently within renovated neighborhoods situated in major cities compared to other areas. However, this effect is expected to be relatively smaller in comparison to non-renovated neighborhoods located within big cities that did not undergo significant demolitions.

These expectations are reinforced by Graph 4.1, which reveals a more adverse economic condition within treated units compared to control ones. Besides, the graph illustrates a steeper slope in control neighborhoods situated in big cities compared to those in France (indicating greater income growth in the last decile over the period studied). As anticipated, treated neighborhoods in big cities appear to experience an intermediate scenario, with a steeper slope than control units in France but a relatively milder slope than those in the same big cities.




Graph 4.1 Evolution of the median and last decile in treated and control neighborhoods

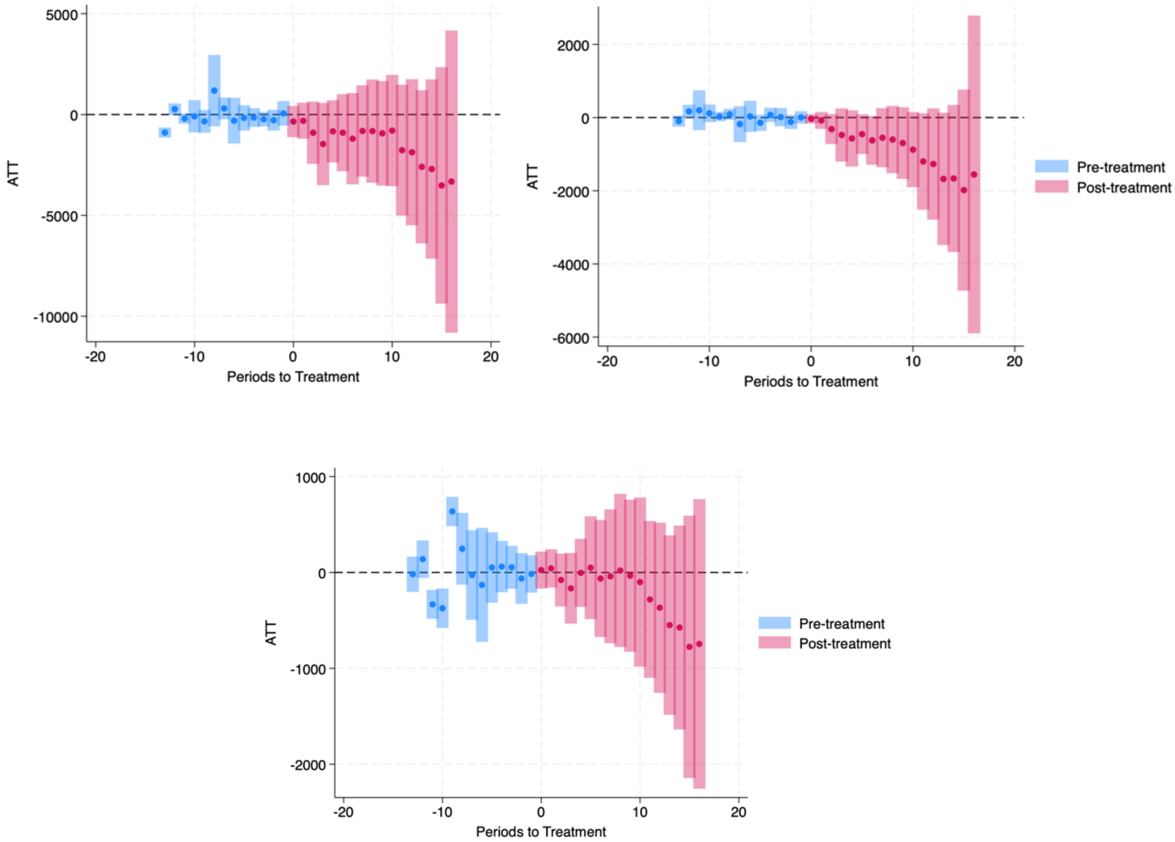
## Results

### Impact of the PNRU on the number of households

Regarding the number of households, I find a significant increase in treated neighborhoods located in big cities as the result of the PNRU law compared to all control units. Given the nature of the treatment, such a finding seems counterintuitive. One might assume that the increase in the number of households in the neighborhoods is mainly due to the private housing stock: there are more households in the neighborhoods, but not in the social housing, as these have been demolished. In addition, I assume that the increase in households actually corresponds to an increased demand in housing supply at the periphery of the neighborhood that I unfortunately capture as the number of households is originally calculated at the IRIS level.

### Impact of the PNRU on the income distribution

When comparing the impact of the law on the income distribution between treated neighborhoods located in big cities and control neighborhoods located in metropolitan France, I find a decline in the Gini index similar to the one found in the global treatment effect part, though not significant. At this stage, I cannot not reach any conclusions regarding income inequality within treated neighborhoods located in big cities. Besides, I observe that the median, first and last deciles increase within treated neighborhoods located in big cities as the result of the program, though not in a significant way (refer to Table 4.1). Compared to previous findings, it is the first time that I observe a joint increase in the income of the poorest and richest residents, reflecting gentrification. It therefore seems that due to the PNRU the overall level of poverty has decreased relatively more in treated neighborhoods located in big cities than in untreated ones located in France. This finding confirms the precedent assumption according to which the renovation can more easily attract rich households when located in a valuable area. However, comparing treated neighborhoods in big cities with untreated ones in metropolitan France might not be the most relevant approach. Although fixed effects exist to ensure the econometric comparison is accurate, the interpretation from a public policy standpoint is less straightforward. For policymakers, a more sensible approach would involve comparing treated and untreated neighborhoods all situated within the same four major cities. This is precisely what I am accomplishing with the CSDID estimator. I still find no significant effect of the PNRU on income inequality using the Gini coefficient and the inter decile ratio. On the other hand, I find negative coefficients for the median, first and last deciles that prove to be significant for the first variable. In the absence of the PNRU program within big cities, the median income would have increased by an average of 697 euros at a 90% confidence interval (refer to Table 4.2). The phenomenon of gentrification is thus stronger in untreated neighborhoods located in big cities, where rich households have probably preferred to settle in neighborhoods that did not undergo disruptive work. As for the poorest households, as the share of poor households is still higher in renovated neighborhoods, I assume that these neighborhoods still face a more pronounced avoidance phenomenon.




Footnote: regression on the last decile is shown at top left, on median income at top right and on the first decile at the bottom

Graph 4.2 Causal impacts of the PNRU on the last decile, median income, and first decile per consumption unit using the classification (CSDID estimator)

# Conclusion

The PNRU law, adopted in 2003, aimed at integrating deprived urban areas within their urban environment. This ambition is translated through the stated objective of promoting social mix through the reduction of inequalities between places and populations. In this study, I evaluate the impact of the law on income distribution at the neighborhood level, arguing in favor of the need for a more socially diversified population composition within neighborhoods.

For such a purpose, I utilize the difference-in-differences method relying on a standard TWFE and the CSDID estimator. I compare the evolution of renovated neighborhoods to the one of non-targeted neighborhoods under the assumption that their evolutions would have been parallel in the absence of the program. This assumption is entirely credible as the data indicate that the evolution in the outcome of interest between targeted and non-targeted neighborhoods are parallel in the pre-treatment period. I measure the impact of the policy on income distribution using a two-ways-fixed-effects regression as well as the Callaway and Sant Anna estimator to consider the staggered nature in the treatment. After measuring the global treatment effect, I control for heterogeneities in the nature and intensity of the treatment and ultimately in the location characteristics of the neighborhoods.

I first measure the impact of the law on the number of households within neighborhoods. As predicted, I observe a significant decline in the short run which can be attributed to demolition and rehabilitation operations that led to the temporary increase in vacancy rate. The most heavily demolished neighborhoods witness a persistent decline in the number of households. As these neighborhoods are generally also those with the worst socioeconomic situation, the ANRU has probably decided to spatially desegregate these neighborhoods by rebuilding social housing elsewhere (in another ZUS or within the urban unit) in addition to a relatively high on-site supply. In her paper, Guyon indicates that not all the indicators of the attractiveness of renovated neighborhoods have turned green: in 2013, the vacancy rate remains relatively high, suggesting an avoidance phenomenon, and despite a decrease in the share of households belonging to the first decile, their number remain relatively high in absolute terms compared to the national level (Guyon, 2016).

I also measure income inequality within neighborhoods using the Gini index. I find a global decline equal to -.007 on average over the post-treatment period, all else equal. However, in the medium term the coefficient reaches pre-treatment levels suggesting that the changes are mainly explained by the operations conducted which led to temporary departures. Nonetheless, within heavily demolished and reconstructed neighborhoods the decline more than doubles to reach -0.02 and is persistent over time, approximating -.007 in the long run. I therefore grant particular importance to demolition and on-site reconstruction for diminishing income inequality within neighborhoods. These findings are aligned with Guyon and France Stratégie's note who both indicate a stronger impact of the PNRU in highly demolished neighborhoods (Guyon, 2016 ; France Stratégie and Guyon, 2024).

Besides, controlling for heterogeneity in the treatment, I find that the shift in the income distribution differs across neighborhoods based on a different nature and intensity in operations. Within heavily demolished and reconstructed neighborhoods, the income distribution is concentrated more closely around central values as a result of the law due to a significant decline in the income of the last decile as well as a significant increase in the income of the first decile. Demolitions mostly targeted poor households causing their temporary departure. As shown by Guyon, the share of households belonging to the second and third quartiles has increased due to the PNRU, suggesting that the poorest were then replaced by slightly richer residents (Guyon, 2016). Regarding the wealthiest, I assume that disruptive work has eventually forced them to leave. In neighborhoods where rehabilitation and residentialization operations were the main ones, the median income decreases despite the departure of the poorest households. As I regress on the income directly (and not the proportion of households belonging to deciles), I observe that the decline in the last decile outbids the increase in the first decile income, ultimately leading to a decrease in the median income within renovated neighborhoods. Yet, note that the number of rich households who left can be smaller compared to the one of the poorer households. Within low intensity treated neighborhoods, the income distribution is more centered towards lower deciles as a result of the law driven by a decrease in the highest decile, ultimately decreasing the median income per consumption unit. Contrary to highly demolished neighborhoods where the poorest had to leave massively, I do not find any impact of the law on the first decile in these neighborhoods suggesting their continued presence. I deduce that the exodus of the wealthiest within poorly renovated neighborhoods also occurred due to disruptive work.

Ultimately, I measure the impact of the PNRU within the four main cities in France. I observe that the PNRU has diminished poverty within renovated neighborhoods situated in major cities compared to all non-renovated neighborhoods. However, these renovated units experienced less gentrification compared to what would have occurred in the absence of the program when juxtaposed with neighborhoods exclusively located in major cities.

## Policy recommendations

A decrease in intra-neighborhood income inequalities does not necessarily imply a more favorable socioeconomic situation within neighborhoods. On the contrary, the reduction in income distribution as the result of the PNRU law implies a stronger concentration of lower-middle incomes, especially within low-intensity treated neighborhoods. On the one hand, the lowest incomes have been displaced from the neighborhoods due to demolition operations. The increase in the first decile could have been explained by an improvement in the living conditions of the poorest but this situation seems improbable and Guyon shows that the share of households belonging to the first decile decreases due to the PNRU (Guyon, 2016). We do not know where they have gone, but in any case, this means that they do not benefit from the supposed benefits of the PNRU within neighborhoods, which encourage better cultural, employment, and educational opportunities. Furthermore, the departure of the wealthiest due to renovation works is problematic as it fosters the clustering of lower-middle classes within the neighborhoods. With the support of the causal impacts found in this study, I therefore formulate the following recommendations:

**Promoting income diversity within neighborhoods**

The program aims at integrating neighborhoods within their urban environment by diminishing inequalities across populations and places. I argue in favor of a similar decrease in spatial inequalities at the neighborhood level. Indeed, this study reveals that the PNRU program has reinforced the concentration of poorer residents in low-renovated neighborhoods. Within heavily renovated neighborhoods, the concentration of incomes has concentrated towards more central values but still around relatively low deciles.

**Ensuring social housing for the poorest households**

The imperative to desegregate spatially concentrated low-income neighborhoods should not overshadow the crucial need to address the welfare of the most impoverished residents, who deserve access to adequate housing. One should augment the availability of social housing for the most vulnerable individuals outside renovated areas. This approach aims to reshape the social fabric of the renovated neighborhoods while ensuring that the needs of the poorest are met. The NPNRU (the "New" PNRU) has prevented the reconstruction of social housing on-site which is perceived as a hindrance to changes in social composition within neighborhoods. Evaluating this renewed program should specify this recommendation.

**Enhance complementarity of urban laws in France**

The PNRU may legitimately seek to attract households with relatively higher incomes to avoid spatial segregation of the lowest incomes. However, as stated in the previous recommendation, it is also necessary to consider the relocation of the most disadvantaged. To this end, it would be possible to mobilize the SRU law, which aims to introduce 25% social housing in municipalities with more than 3,500 inhabitants (1,500 in the Paris metropolitan area) belonging to an urban area. However, it is important to maintain within this law a portion of social housing guaranteed to households with the lowest incomes and not to allocate social housing only to intermediate incomes.

**Targeting the new buyers to influence the population composition within neighborhoods**

The housing units for sale in the renovated neighborhoods should target owner-occupiers. Since landlords seek financially solvent individuals, this targeting will primarily concern households with relatively high resources. This intervention must be complementary to interventions in the social housing sector to ensure that the poorest are not excluded. Furthermore, it will prevent the sale of new homes to landlord owners who may turn out to be slumlords renting out properties to vulnerable individuals at exorbitant prices.[25]

**Encouraging spillover effects within neighborhoods**

In addition to the need to intervene in the social composition of neighborhoods, it is also important to create spaces in these neighborhoods that promote social integration within the

[25] Interview with Marina Lagune, former head of cross-functional housing policies at the DRIHL

neighborhood and more broadly within the city. The NPNRU indeed recognizes the need to provide more local public goods, through the construction of daycare centers, schools, libraries, shops, and other public services, as well as bus lines to integrate the neighborhoods into their urban space. This objective ultimately aims to promote the socio-economic capital gain of residents.

## To go further

In the estimation strategy, there are several limitations that warrant consideration. These limitations underscore the complexity inherent in estimating the impacts of urban renewal policies and highlight avenues for further refinement and exploration in future research endeavors. Firstly, it would have been necessary to work with a stable sample throughout the whole study, even if it meant excluding neighborhoods that do not appear in certain databases. Consequently, I am working with samples of varying sizes, which may bias my estimates. In addition, controlling for spillover effects would have also enhanced my study. Control neighborhoods are often geographically proximate to treated neighborhoods, which violates the Stable Unit Treatment Value Assumption (SUTVA). Despite this, I did not specifically address or account for potential spillover effects in my analysis. Finally, while conducting regression analyses at the neighborhood level, I aggregate data from the IRIS level, albeit with weighting. However, it is worth noting that an alternative approach could involve regression analyses directly at the IRIS level, thereby minimizing potential approximations. For instance, I assumed that the neighborhood-level Gini coefficient necessarily equated to the sum of Gini coefficients at the IRIS level, but this may not always hold true. Consequently, any observed reduction in inequalities at the neighborhood level may not necessarily imply a similar decrease in inequalities at the IRIS level.

Building upon the identified limitations, I now outline potential improvements to enhance the study. There is scope for enhancing my evaluation of the PNRU law the utilization of inequality indices beyond the conventional Gini coefficient and inter-decile ratio. Exploring more sophisticated inequality measures could yield deeper insights into the effects of urban renewal policies such as the PNRU. Indeed, it might be worthwhile to conduct a dedicated study evaluating the PNRU's impact solely through the lens of inequality indicators. Furthermore, the estimator proposed by Callaway and Sant Anna provides additional insights into the average treatment effect on the treated that were not leveraged in this study. For example, it offers the ability to assess whether treatment effects vary across different cohorts. In my case, this could have facilitated an examination of whether early treated neighborhoods predominantly drove the treatment effect.

To further investigate the impact of urban renewal policies such as the PNRU, several avenues for analysis could be pursued. Conducting a comparative analysis across neighborhoods, rather than solely within neighborhoods, could provide valuable insights into the broader impact of the PNRU. Replicating the analysis at the individual level also presents an opportunity to track residents' movements and location choices over time. This approach would enable the measurement of changes in the composition of residents within and across neighborhoods, including the ratio of pre- and post-operation residents, as well as the influx of new residents. Such an evaluation could notably elucidate whether the persistent increase in income among residents in the lowest decile leads to improvements in living conditions for households reintegrating neighborhoods post-demolition, or if they are replaced by households with medium incomes. Furthermore, enhancing the evaluation of neighborhood attractiveness by incorporating rent data could provide valuable insights into changes in housing demand and affordability following urban renewal initiatives. Lastly, shifting towards evaluating the NPNRU (New National Urban Renewal Program) presents an opportunity to measure changes in policy implementation, particularly regarding the prohibition of on-site reconstruction. This prohibition aims to ensure genuine revitalization and spatial desegregation of income groups. By examining the impact of the location of reconstruction, particularly focusing on areas outside deprived neighborhoods, one can better understand the effects of policy decisions on neighborhood dynamics and social composition.

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# Annex

## Tables

Table 0.1. Descriptive Statistics for Control and Not-yet Treated Units in 2002

**Descriptive Statistics : Control Units in 2002**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| number housing units | 408 | 1250.425 | 1704.258 | 4.239 | 20766.521 |
| number of household | 366 | 1014.876 | 1325.445 | .312 | 14314.813 |
| area | 410 | 394589.27 | 408685.56 | 3369.78 | 3146311.4 |
| density | 366 | 3005.003 | 3273.278 | 7.345 | 26537.924 |
| gini coefficient | 348 | .352 | .069 | .013 | .578 |
| inter decile | 342 | .104 | .123 | .01 | .97 |
| q2 | 351 | 10767.989 | 2882.823 | 0 | 18649.557 |
| d1 | 342 | 3163.565 | 1592.261 | 48.166 | 8980.126 |
| d9 | 348 | 21681.368 | 5360.669 | 715.918 | 42190.973 |

**Descriptive Statistics : Not-yet-treated units in 2002**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| number housing units | 527 | 2230.975 | 2583.474 | 2.246 | 29317.713 |
| number of household | 507 | 1827.86 | 2032.117 | 5.346 | 19665.684 |
| area | 529 | 638072.96 | 732845.58 | 6792.097 | 8141016.6 |
| density | 507 | 3031.025 | 2433.086 | 40.197 | 24326.855 |
| gini coefficient | 485 | .353 | .075 | .005 | .779 |
| inter decile | 475 | .107 | .101 | .01 | .819 |
| q2 | 487 | 9739.077 | 2768.324 | 123.899 | 26913.643 |
| d1 | 475 | 2573.551 | 1474.197 | 22.581 | 8587.767 |
| d9 | 485 | 19840.906 | 5106.21 | 259.475 | 57930.523 |

Table 0.2. Type of operations

| Type of operations | ANRU subsidies (in million euros) |
|---|---|
| Demolition of social housing | 2,320 |
| Production of social housing | 2,280 |
| Change of use of social housing | 9,1 |
| Requalification of degraded urban blocks | 135 |
| Rehabilitation of social housing | 1,150 |
| Residentialisation of social housing | 687 |
| Improvement of service quality in social housing | 98,8 |
| Urban planning | 1,640 |
| Public facilities | 1,170 |
| Commercial or artisanal spaces | 96,6 |
| Intervention on private housing | 248 |
| Project Management / Engineering | NA |

Table 1.1. TWFE regression using 2003 as treatment date

| | (1) households | (2) Gini | (3) inter-decile | (4) d1 | (5) q2 | (6) d9 |
|---|---|---|---|---|---|---|
| Post * Treat | -12.70 | -0.00734*** | 0.00282 | 20.66 | -213.0* | -697.3*** |
| | (-0.82) | (-3.74) | (0.36) | (0.35) | (-2.36) | (-4.26) |
| Constant | 1518.2*** | 0.367*** | 0.148*** | 2748.0*** | 12074.0*** | 24933.6*** |
| | (181.34) | (341.99) | (34.35) | (84.59) | (243.60) | (277.08) |
| N | 16214 | 14107 | 14554 | 14604 | 15084 | 14941 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.2. TWFE regression using year of first work as treatment date

| | (1) households | (2) Gini | (3) inter-decile | (4) d1 | (5) q2 | (6) d9 |
|---|---|---|---|---|---|---|
| Post*Treated | -4.167 | -0.00514** | -0.00905 | 171.1** | -32.68 | -32.46 |
| | (-0.26) | (-2.59) | (-1.60) | (3.03) | (-0.37) | (-0.18) |
| Constant | 1513.3*** | 0.365*** | 0.154*** | 2679.1*** | 11972.4*** | 24565.6*** |
| | (204.87) | (398.47) | (58.41) | (101.00) | (289.33) | (286.85) |
| N | 16214 | 14107 | 14554 | 14604 | 15084 | 14941 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.3. CSDID estimator on the number of households

| ATT on Households | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -12.579 | 15.619 | -0.810 | 0.421 | -43.191 | 18.034 | | |

| ATT on Households by Calendar Period Coefficient (from 2003 to 2019) | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| Ave -26.883 | 9.086 | -2.960 | 0.003 | -44.692 | -9.074 | | |
| -15.887 | 6.596 | -2.410 | 0.016 | -28.814 | -2.960 | | |
| -20.236 | 5.024 | -4.030 | 0.000 | -30.082 | -10.390 | | |
| -35.655 | 6.002 | -5.940 | 0.000 | -47.420 | -23.891 | | |
| -46.661 | 6.330 | -7.370 | 0.000 | -59.067 | -34.255 | | |
| -23.950 | 10.314 | -2.320 | 0.020 | -44.165 | -3.736 | | |
| -32.122 | 10.642 | -3.020 | 0.003 | -52.981 | -11.263 | | |
| -52.232 | 13.211 | -3.950 | 0.000 | -78.124 | -26.339 | | |
| -56.050 | 13.745 | -4.080 | 0.000 | -82.989 | -29.111 | | |
| 4.498 | 20.534 | 0.220 | 0.827 | -35.748 | 44.745 | | |
| -0.880 | 21.818 | -0.040 | 0.968 | -43.642 | 41.882 | | |
| 2.005 | 22.878 | 0.090 | 0.930 | -42.836 | 46.846 | | |
| 5.946 | 23.341 | 0.250 | 0.799 | -39.802 | 51.693 | | |
| 8.592 | 24.079 | 0.360 | 0.721 | -38.601 | 55.786 | | |
| 8.920 | 25.319 | 0.350 | 0.725 | -40.706 | 58.545 | | |
| 13.859 | 26.164 | 0.530 | 0.596 | -37.421 | 65.139 | | |
| 17.451 | 26.932 | 0.650 | 0.517 | -35.335 | 70.238 | | |

Table 1.4. CSDID estimator on Gini coefficient, inter decile ratio, D1, Q2, D9.

| ATT on Gini | Std. | err | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.007 | 0.002 | -3.440 | 0.001 | -0.011 | -0.003 | | |

| ATT on inter-decile ratio | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.004 | 0.007 | -0.590 | 0.555 | -0.018 | 0.010 | | |

| ATT on d1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 44.384 | 53.994 | 0.820 | 0.411 | -61.442 | 150.210 | | |

| ATT on d9 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -593.893 | 161.592 | -3.680 | 0.000 | -910.608 | -277.178 | | |

| ATT on q2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -223.933 | 86.738 | -2.580 | 0.010 | -393.937 | -53.929 | | |

Table 2.1. Share of neighborhoods per intensity in terms of demolition and construction

| | | On-site construction intensity | | | Total |
|---|---|---|---|---|---|
| | | Low | Medium | High | |
| **Demolition intensity** | Low | 102 | 32 | 13 | 147 |
| | Medium | 44 | 98 | 24 | 166 |
| | High | 14 | 31 | 122 | 167 |
| Total | | 160 | 161 | 151 | 480 |

Legend: In pink, Neighborhoods that have witnessed heavy demolitions but low on-site construction. In blue, Neighborhoods that have witnessed heavy demolitions and on-site constructions. Among these 122 neighborhoods, 92 have witnessed heavy rehabilitation operations and thus belong to the housing-intensive subgroup.

Table 2.2. Subgroups based on different intensity in the treatment

| Groups | Characteristics | Average demol | Average constr | Average rehab | Number of neighborhoods |
|---|---|---|---|---|---|
| Demolition and construction intensive | The top third of neighborhoods that have undergone intensive demolitions (> 24%) and the top third of neighborhoods that undergone constructions on-site (> 11%) | 62,31% | 33,94% | 43,57% | 122 |
| Housing intensive | Neighborhoods in the first group, which also experienced rehabilitation of over 12%. | 56,85% | 29,34% | 57,49% | 92 |
| Relatively intensive demolition and low construction on site or Relatively low intensity | Refer to Table 2.1 | 29,30% | 3,31% | 42,42% | 89 |

Table 2.3. Causal impact of the PNRU on the number households in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -4.167 | 21.25 | 10.37 | 14.33 |
| | (-0.26) | (1.12) | (0.58) | (0.80) |
| Heavy demol x constr | | -126.4*** | | |
| | | (-5.61) | | |
| Low renovation | | | -99.40*** | |
| | | | (-3.70) | |
| Housing intensive | | | | -129.9*** |
| | | | | (-5.28) |
| _cons | 1513.3*** | 1515.0*** | 1514.7*** | 1515.3*** |
| | (204.87) | (212.01) | (210.75) | (211.60) |
| N | 16214 | 16214 | 16214 | 16214 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.4. Causal impact of the PNRU on the Gini index in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -0.00514** | -0.00221 | -0.00502* | -0.00347 |
| | (-2.59) | (-1.01) | (-2.32) | (-1.64) |
| Heavy demol x constr | | -0.0151*** | | |
| | | (-3.43) | | |
| Low renovation | | | -0.000811 | |
| | | | (-0.22) | |
| Housing intensive | | | | -0.0117* |
| | | | | (-2.26) |
| Constant | 0.365*** | 0.366*** | 0.365*** | 0.366*** |
| | (398.47) | (400.90) | (402.93) | (399.02) |
| N | 14107 | 14107 | 14107 | 14107 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.5. Causal impact of the PNRU on the inter decile ratio in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -0.00905 | -0.00378 | -0.0114 | -0.00687 |
| | (-1.60) | (-0.62) | (-1.91) | (-1.14) |
| Heavy demol x constr | | -0.0271** | | |
| | | (-2.70) | | |
| Low renovation | | | 0.0163 | |
| | | | (1.30) | |
| Housing intensive | | | | -0.0153 |
| | | | | (-1.37) |
| Constant | 0.154*** | 0.154*** | 0.154*** | 0.154*** |
| | (58.41) | (58.94) | (58.25) | (58.79) |
| N | 14554 | 14554 | 14554 | 14554 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.6. Causal impact of the PNRU on the first decile per consumption unit in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | 171.1** | 133.9* | 206.3*** | 155.4* |
| | (3.03) | (2.14) | (3.35) | (2.56) |
| Heavy demol x constr | | 191.5 | | |
| | | (1.92) | | |
| Low renovation | | | -241.7** | |
| | | | (-2.91) | |
| Housing intensive | | | | 110.3 |
| | | | | (1.08) |
| Constant | 2679.1*** | 2677.3*** | 2682.7*** | 2677.8*** |
| | (101.00) | (101.44) | (102.75) | (101.61) |
| N | 14604 | 14604 | 14604 | 14604 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.7. Causal impact of the PNRU on the median income per consumption unit in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -32.68 | -76.63 | 13.00 | -20.06 |
| | (-0.37) | (-0.80) | (0.14) | (-0.21) |
| Heavy demol x constr | | 225.9 | | |
| | | (1.25) | | |
| Low renovation | | | -313.2* | |
| | | | (-2.38) | |
| Housing intensive | | | | -87.57 |
| | | | | (-0.51) |
| _cons | 11972.4*** | 11970.0*** | 11977.4*** | 11973.5*** |
| | (289.33) | (289.58) | (293.50) | (290.93) |
| N | 15084 | 15084 | 15084 | 15084 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.8. Causal impact of the PNRU on the last decile per consumption unit in the three subgroups resulting from the heterogeneity (1) (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -32.46 | 11.89 | 116.6 | 33.94 |
| | (-0.18) | (0.06) | (0.58) | (0.17) |
| Heavy demol x constr | | -229.3 | | |
| | | (-0.68) | | |
| Low renovation | | | -1012.1*** | |
| | | | (-3.78) | |
| Housing intensive | | | | -465.6 |
| | | | (-1.22) | |
| Constant | 24565.6*** | 24567.8*** | 24581.8*** | 24570.9*** |
| | (286.85) | (289.07) | (293.92) | (289.26) |
| N | 14941 | 14941 | 14941 | 14941 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2.9. Causal impact of the PNRU on the number of households, the Gini index, the inter decile, the median income, the first decile and the last decile per consumption unit in the three subgroups resulting from heterogeneity (1) (CSDID estimator)

| ATT on the number of households in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -102.660 | 19.627 | -5.230 | 0.000 | -141.129 | -64.192 | | |

| ATT on the number of households in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -76.494 | 24.649 | -3.100 | 0.002 | -124.806 | -28.182 | | |

| ATT on the number of households in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -114.370 | 24.240 | -4.720 | 0.000 | -161.880 | -66.861 | | |

| ATT on the Gini index in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.020 | 0.004 | -4.750 | 0.000 | -0.028 | -0.012 | | |

| ATT on the Gini index in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.005 | 0.003 | -1.660 | 0.097 | -0.011 | 0.001 | | |

| ATT on the Gini index in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.018 | 0.005 | -3.710 | 0.000 | -0.027 | -0.008 | | |

| ATT on the inter decile ratio in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.032 | 0.013 | -2.470 | 0.014 | -0.058 | -0.007 | | |

| ATT on the inter decile ratio in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 0.011 | 0.014 | 0.790 | 0.431 | -0.016 | 0.038 | | |

| ATT on the inter decile ratio in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.025 | 0.015 | -1.690 | 0.091 | -0.055 | 0.004 | | |

| ATT on the median income per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -25.715 | 159.906 | -0.160 | 0.872 | -339.125 | 287.695 | | |

| ATT on the median income per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -543.745 | 121.847 | -4.460 | 0.000 | -782.560 | -304.930 | | |

| ATT on the median income per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -190.164 | 155.436 | -1.220 | 0.221 | -494.812 | 114.485 | | |

| ATT on the first decile per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 240.621 | 83.117 | 2.890 | 0.004 | 77.715 | 403.528 | | |

| ATT on the first decile per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -176.111 | 69.855 | -2.520 | 0.012 | -313.025 | -39.198 | | |

| ATT on the first decile per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 202.175 | 84.977 | 2.380 | 0.017 | 35.624 | 368.726 | | |

| ATT on the last decile per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -693.003 | 306.898 | -2.260 | 0.024 | -1294.512 | -91.494 | | |

| ATT on the last decile per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -1338.349 | 224.966 | -5.950 | 0.000 | -1779.274 | -897.423 | | |

| ATT on the last decile per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -802.024 | 341.897 | -2.350 | 0.019 | -1472.131 | -131.918 | | |

Footnote: Group 1 corresponds to highly demolished and on-site reconstructed neighborhoods, Group 2 corresponds to relatively low intensive neighborhoods, and Group 3 is a subgroup of Group 1 with housing-intensive neighborhoods.

Table 3.1. Presentation of the subgroups of the classification

| | Proportion of neighborhood | Demolition | Construction | Rehab | Resid | Services | Planning | Facilities |
|---|---|---|---|---|---|---|---|---|
| Group 1 | .507 | .093 | .089 | 0.196 | .153 | .018 | .051 | .072 |
| Group 2 | .244 | .208 | .133 | 0.569 | .756 | .032 | .085 | .115 |
| Group 3 | .248 | .625 | .552 | 0.420 | .407 | .05 | .142 | .347 |

Table 3.2. Causal impact of the PNRU on the number households in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -4.167 | | | |
| | (-0.26) | | | |
| Group 1 | | 33.01 | | |
| | | (1.26) | | |
| Group 2 | | | -30.32 | |
| | | | (-1.68) | |
| Group 3 | | | | -84.59*** |
| | | | | (-6.34) |
| Constant | 1513.3*** | 1682.2*** | 1149.6*** | 961.0*** |
| | (204.87) | (198.62) | (310.29) | (366.85) |
| N | 16214 | 11724 | 9241 | 9101 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is madeup of heavily demolished and reconstructed neighborhoods.

Table 3.3. Causal impact of the PNRU on the Gini index in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -0.00514** | | | |
| | (-2.59) | | | |
| Group 1 | | -0.00460* | | |
| | | (-2.17) | | |
| Group 2. | | | -0.000585 | |
| | | | (-0.14) | |
| Group 3 | | | | -0.0194*** |
| | | | | (-4.41) |
| Constant | 0.365*** | 0.368*** | 0.367*** | 0.364*** |
| | (398.47) | (524.34) | (404.63) | (448.68) |
| N | 14107 | 10211 | 8010 | 7644 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is made up of heavily demolished and reconstructed neighborhoods.

Table 3.4. Causal impact of the PNRU on the inter decile ratio in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*treat | -0.00905 | | | |
| | (-1.60) | | | |
| Group 1 | | 0.000987 | | |
| | | (0.15) | | |
| Group 2 | | | -0.00358 | |
| | | | (-0.36) | |
| Group 3 | | | | -0.0401*** |
| | | | | (-3.60) |
| Constant | 0.154*** | 0.147*** | 0.149*** | 0.154*** |
| | (58.41) | (64.62) | (70.82) | (73.61) |
| N | 14554 | 10564 | 8212 | 7890 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is made up of heavily demolished and reconstructed neighborhoods.

Table 3.5. Causal impact of the PNRU on the median income per consumption unit in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -32.68 | | | |
| | (-0.37) | | | |
| Group 1 | | -138.7 | | |
| | | (-1.20) | | |
| Group 2 | | | -221.8 | |
| | | | (-1.71) | |
| Group 3. | | | | 160.3 |
| | | | | (0.88) |
| Constant | 11972.4*** | 12235.2*** | 12367.4*** | 12337.1*** |
| | (289.33) | (317.14) | (440.30) | (359.32) |
| N | 15084 | 10908 | 8568 | 8208 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is made up of heavily demolished and reconstructed neighborhoods.

Table 3.6. Causal impact of the PNRU on the first decile per consumption unit in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | 171.1** | | | |
| | (3.03) | | | |
| Group 1 | | 49.26 | | |
| | | (0.85) | | |
| Group 2 | | | 157.6 | |
| | | | (1.13) | |
| Group 3. | | | | 433.5*** |
| | | | | (4.43) |
| Constant | 2679.1*** | 2826.2*** | 2904.6*** | 2908.0*** |
| | (101.00) | (144.52) | (97.83) | (157.38) |
| N | 14604 | 10601 | 8233 | 7908 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is made up of heavily demolished and reconstructed neighborhoods

Table 3.7. Causal impact of the PNRU on the last decile per consumption unit in the three subgroups resulting from the classification (TWFE regressor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post*Treat | -32.46 | | | |
| | (-0.18) | | | |
| Group 1 | | -211.5 | | |
| | | (-1.04) | | |
| Group 2 | | | -115.8 | |
| | | | (-0.27) | |
| Group 3 | | | | -363.0 |
| | | | | (-1.12) |
| Constant | 24565.6*** | 25202.1*** | 25272.8*** | 25371.4*** |
| | (286.85) | (370.06) | (271.72) | (416.97) |
| N | 14941 | 10813 | 8483 | 8097 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: Group 1 corresponds to low intensity neighborhoods, Group 2 to heavily rehabilitated and residentialised neighborhoods, Group 3 is made up of heavily demolished and reconstructed neighborhoods.

Table 3.8. Causal impact of the PNRU on the number of households, the Gini index, the inter decile, the median income, the first decile and the last decile per consumption unit in the three subgroups resulting from the classification (CSDID estimator)

| ATT on the number of households in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -97.541 | 15.725 | -6.200 | 0.000 | -128.362 | -66.720 | | |

| ATT on the Gini index in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.021 | 0.004 | -5.030 | 0.000 | -0.029 | -0.013 | | |

| ATT on the inter decile ratio in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.036 | 0.013 | -2.870 | 0.004 | -0.061 | -0.012 | | |

| ATT on the median income per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 13.832 | 158.791 | 0.090 | 0.931 | -297.392 | 325.056 | | |

| ATT on the first decile per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 356.974 | 89.623 | 3.980 | 0.000 | 181.315 | 532.632 | | |

| ATT on the last decile per consumption unit in Group 3 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -576.007 | 313.257 | -1.840 | 0.066 | -1189.978 | 37.965 | | |

| ATT on the number of households in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -46.255 | 18.359 | -2.520 | 0.012 | -82.238 | -10.272 | | |

| ATT on the Gini index in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.002 | 0.003 | -0.640 | 0.525 | -0.009 | 0.004 | | |

| ATT on the inter decile ratio in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.009 | 0.014 | -0.600 | 0.550 | -0.037 | 0.020 | | |

| ATT on the first decile per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 79.030 | 83.591 | 0.950 | 0.344 | -84.805 | 242.865 | | |

| ATT on the median income per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -282.844 | 111.352 | -2.540 | 0.011 | -501.089 | -64.598 | | |

| ATT on the last decile per consumption unit in Group 2 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| -464.873 | 255.014 | -1.820 | 0.068 | -964.692 | 34.946 |

| ATT on the number of households in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 40.866 | 23.929 | 1.710 | 0.088 | -6.035 | 87.767 | | |

| ATT on the Gini index in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.004 | 0.002 | -1.790 | 0.074 | -0.008 | 0.000 | | |

| ATT on the inter decile ratio in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 0.011 | 0.008 | 1.330 | 0.184 | -0.005 | 0.027 | | |

| ATT on the first decile per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -94.992 | 58.766 | -1.620 | 0.106 | -210.171 | 20.187 | | |

| ATT on the median income per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -288.426 | 93.783 | -3.080 | 0.002 | -472.237 | -104.616 | | |

| ATT on the last decile per consumption unit in Group 1 | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -657.835 | 176.478 | -3.730 | 0.000 | -1003.725 | -311.944 | | |

Table 4.1. Causal impact of the PNRU on the number of households, the Gini index, the inter decile ratio, the first decile, the median and the last decile per consumption unit in the four larger French cities (Paris, Marseille, Lyon, Toulouse) (TWFE estimator)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | households | Gini | inter decile | Q2 | D1 | D9 |
| Post*Treat | -22.35 | -0.00434* | -0.00833 | -69.98 | 138.1* | -88.75 |
| | (-1.45) | (-2.09) | (-1.40) | (-0.76) | (2.35) | (-0.47) |
| Big Cities | 198.2* | -0.00828 | -0.00778 | 391.6 | 353.2* | 585.1 |
| | (2.12) | (-1.58) | (-0.79) | (1.84) | (2.52) | (1.07) |
| _cons | 1515.1*** | 0.365*** | 0.154*** | 11976.0*** | 2681.9*** | 24571.0*** |
| | (213.24) | (397.25) | (57.95) | (289.00) | (101.13) | (286.70) |
| N | 16214 | 14107 | 14554 | 15084 | 14604 | 14941 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Footnote: the control group is made up of all untreated neighborhoods (N=410).

Table 4.2. Causal impact of the PNRU on the number of households, the Gini index, the inter decile ratio, the first decile, the median and the last decile per consumption unit in the four larger French cities (Paris, Marseille, Lyon, Toulouse) (CSDID estimator)

| ATT on the number of households | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 129.823 | 100.783 | 1.290 | 0.198 | -67.708 | 327.355 | | |

| ATT on the Gini index | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -0.003 | 0.006 | -0.540 | 0.586 | -0.015 | 0.008 | | |

| ATT on the inter decile ratio | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| 0.012 | 0.016 | 0.750 | 0.454 | -0.020 | 0.044 | | |

| ATT on the median income per consumption unit | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -694.529 | 257.182 | -2.700 | 0.007 | -1198.596 | -190.462 | | |

| ATT on the first decile per | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|

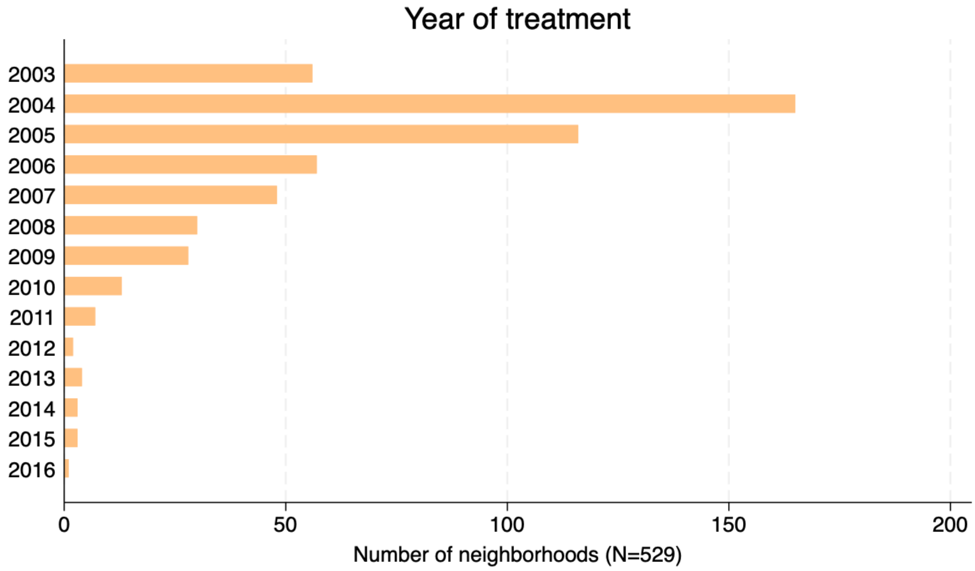
| consumption unit | | | | | | | |
|---|---|---|---|---|---|---|---|
| -127.658 | 144.366 | -0.880 | 0.377 | -410.611 | 155.294 | | |

| ATT on the last decile per consumption unit | Std. | err. | z | P>z | [95% | conf. | interval] |
|---|---|---|---|---|---|---|---|
| -1173.579 | 568.410 | -2.060 | 0.039 | -2287.643 | -59.516 | | |

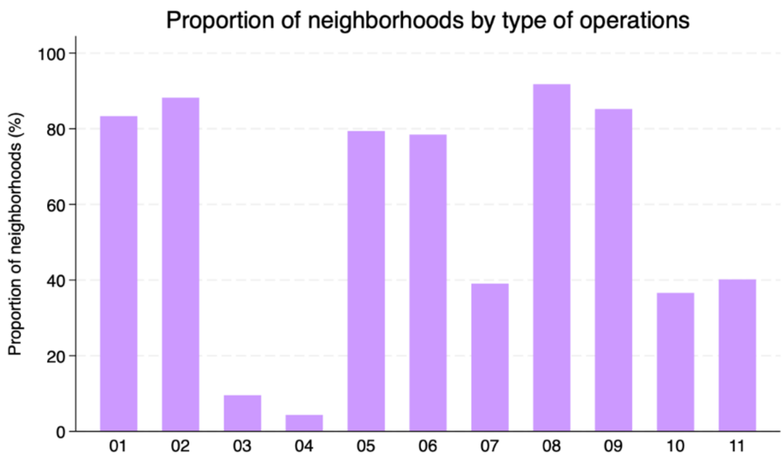
Footnote: the control group is made up of the 53 control neighborhoods located in the same big cities

# Graphs

Graph 0.1. Year of treatment per neighborhood

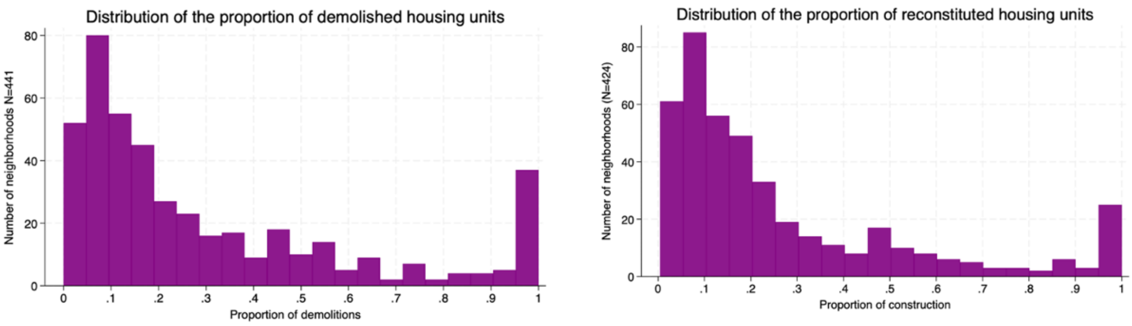



Graph 0.2. Proportion of neighborhoods per type of operations

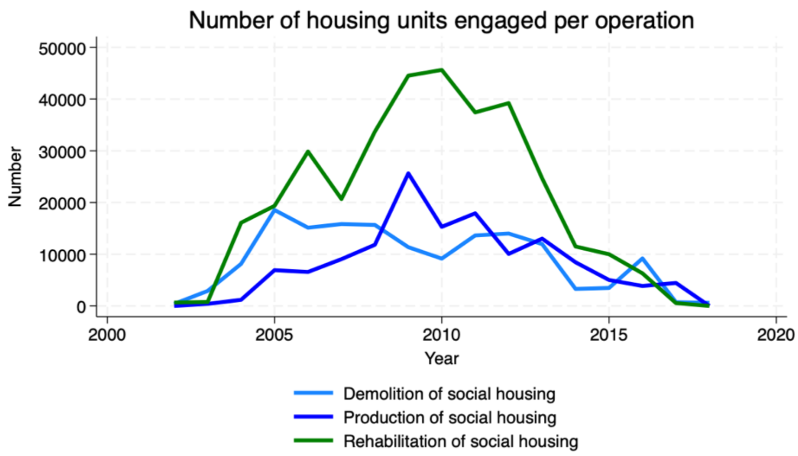



Legend: 01 corresponds to Demolition of social housing, 02 to Production of social housing / Construction, 03 to Change of use of social housing, 04 Requalification of degraded old urban blocks, 05 Rehabilitation of social housing, 06 Residentialization of social housing, 07 Improvement of service quality in social housing, 08 Urban Planning, 09 Public facilities, 10 Commercial or artisanal spaces, 11 Intervention on private housing

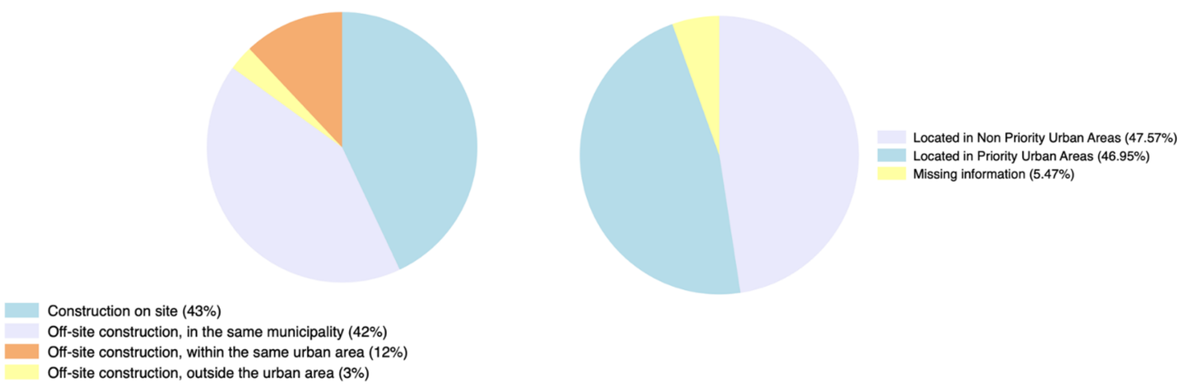
Graph 0.3. Distribution of the proportion of demolished and reconstituted housing units



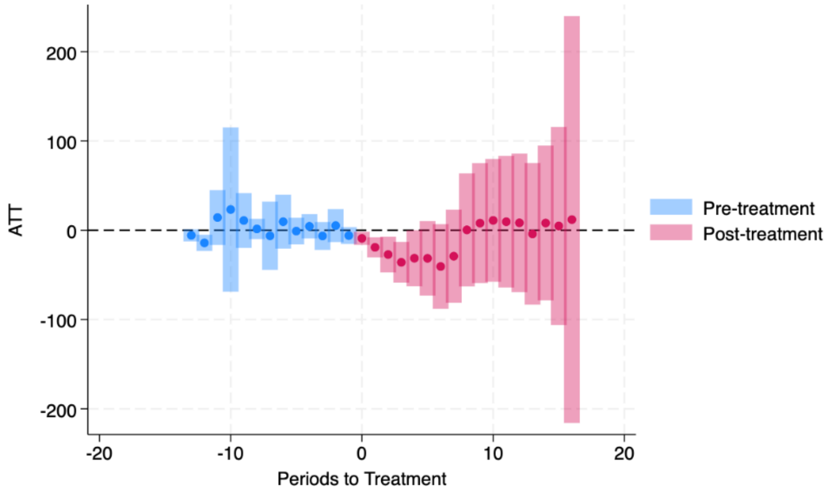

Graph 0.4. Evolution of the number of housing units engaged per operation.



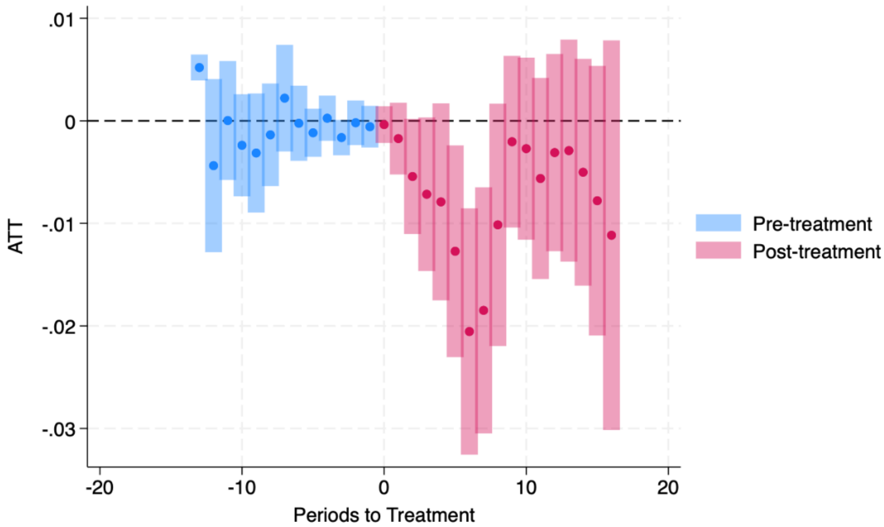

Graph 0.5. Location of the reconstituted social housing supply



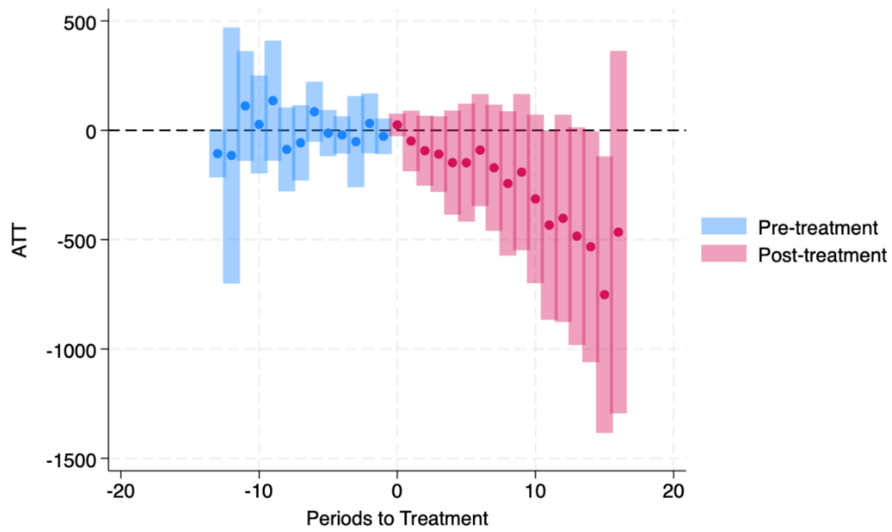
Graph 1.1 Causal impact of the PNRU law on the number of households (CSDID estimator)



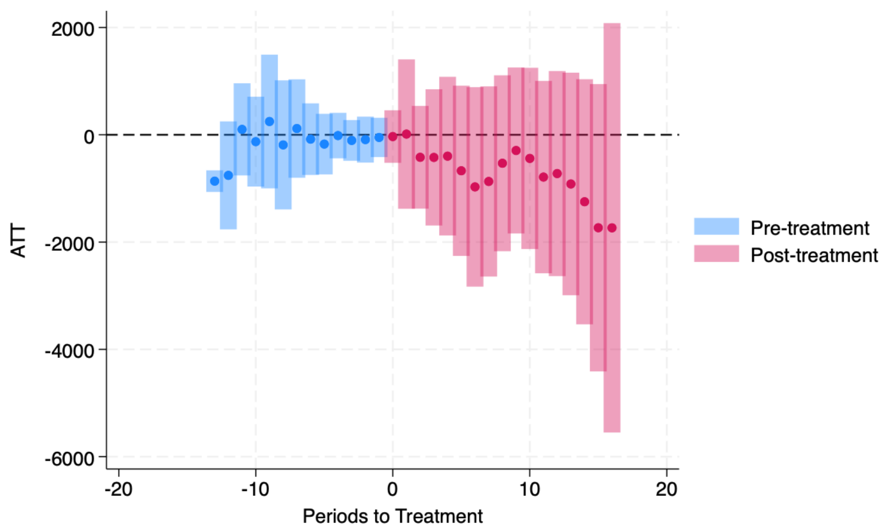

Graph 1.2. Causal impact of the PNRU on the Gini index (CSDID estimator)



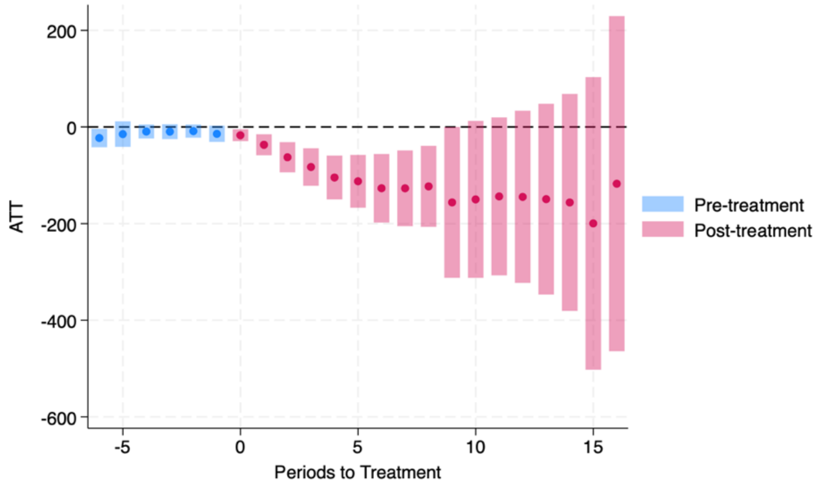
Graph 1.3. Causal impact of the PNRU on the median income per consumption units (CSDID estimator)




Graph 1.4. Causal impact of the PNRU on the last decile (d9) (CSDID estimator)

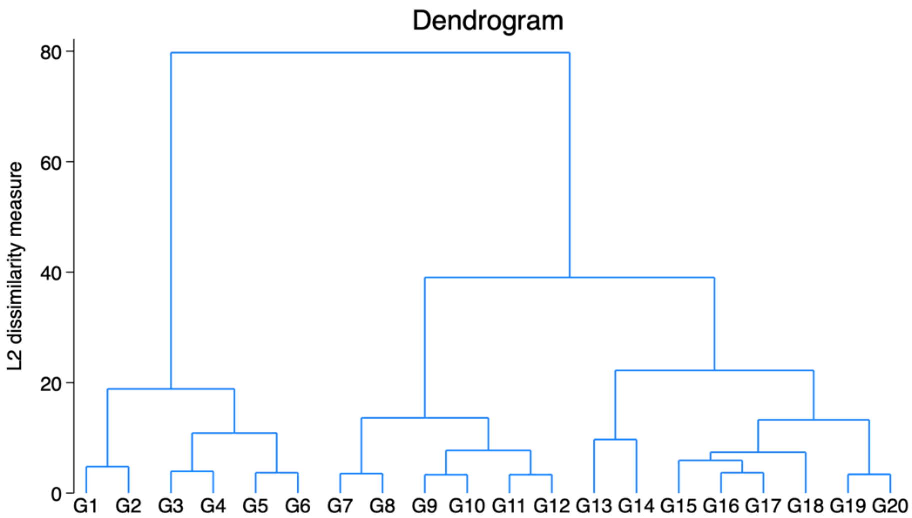


Graph 2.1. Impact of the PNRU on the number of households in the housing-intensive subgroup (CSDID estimator)

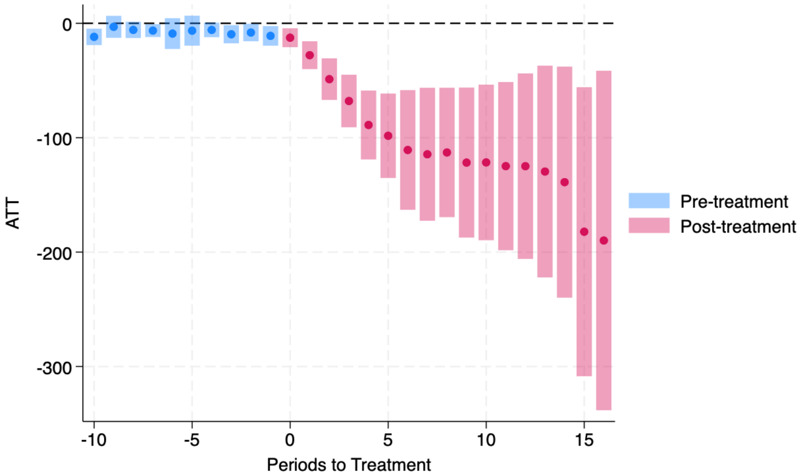



Note: the standard errors increased over time as the sample size decreased.

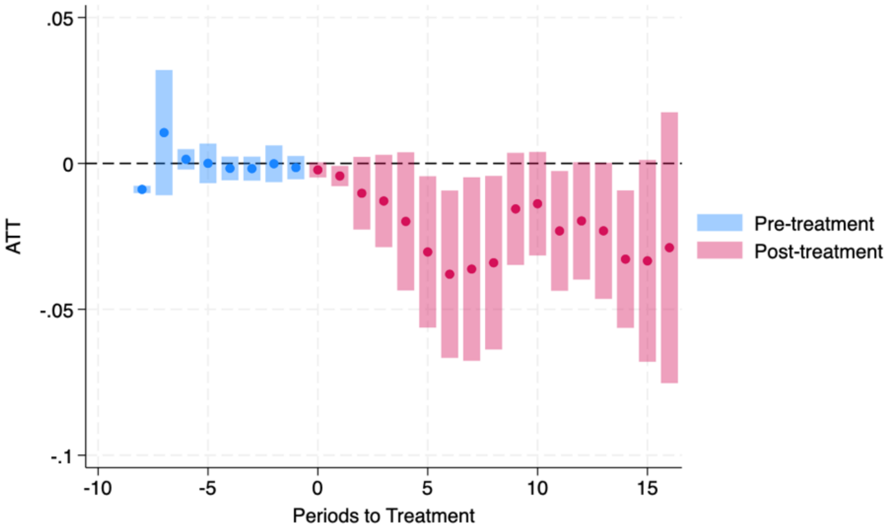
Graph 3.1 Dendrogram



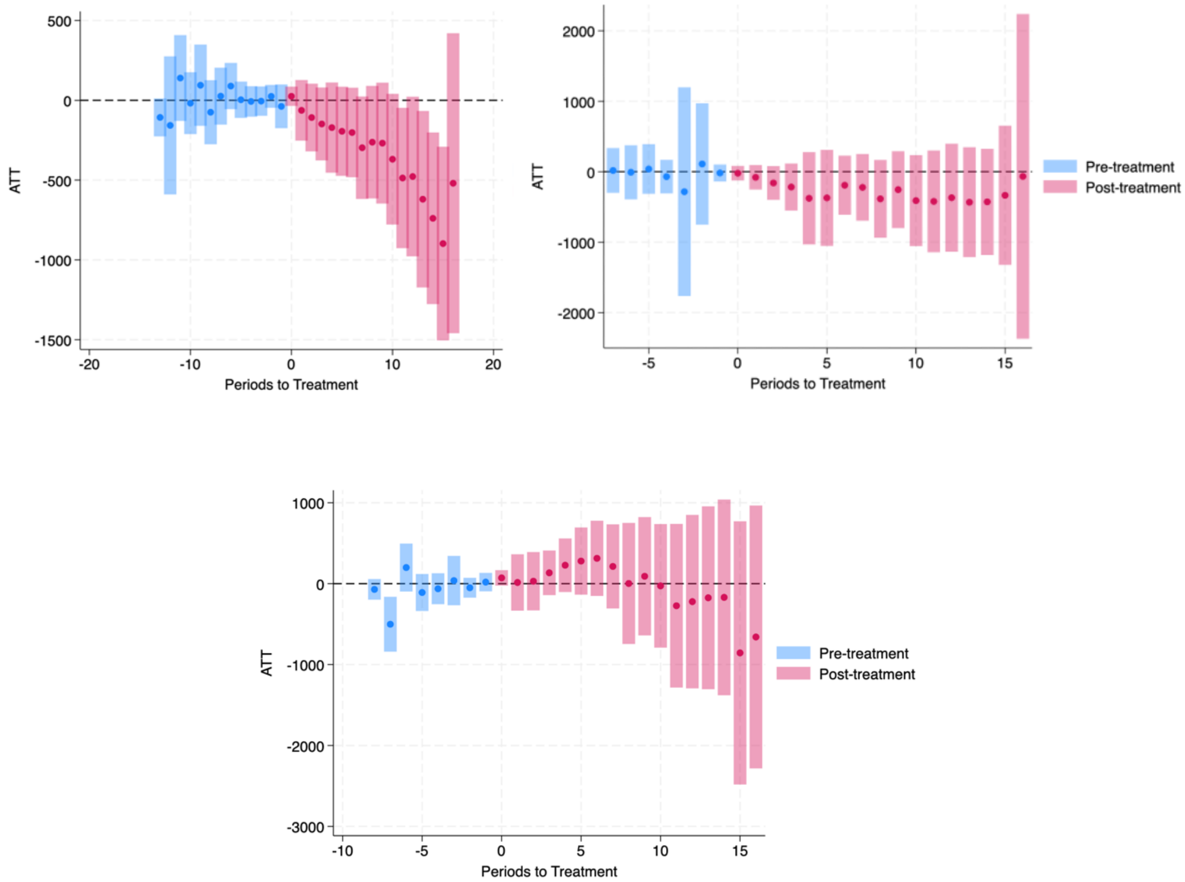
Graph 3.2. Causal impact of the PNRU on the number of households in highly demolished and reconstructed neighborhoods using the classification (CSDID estimator)




Graph 3.3. Causal impact of the PNRU on the Gini coefficient in highly demolished and reconstructed neighborhoods (Group 3) using the classification (CSDID estimator)

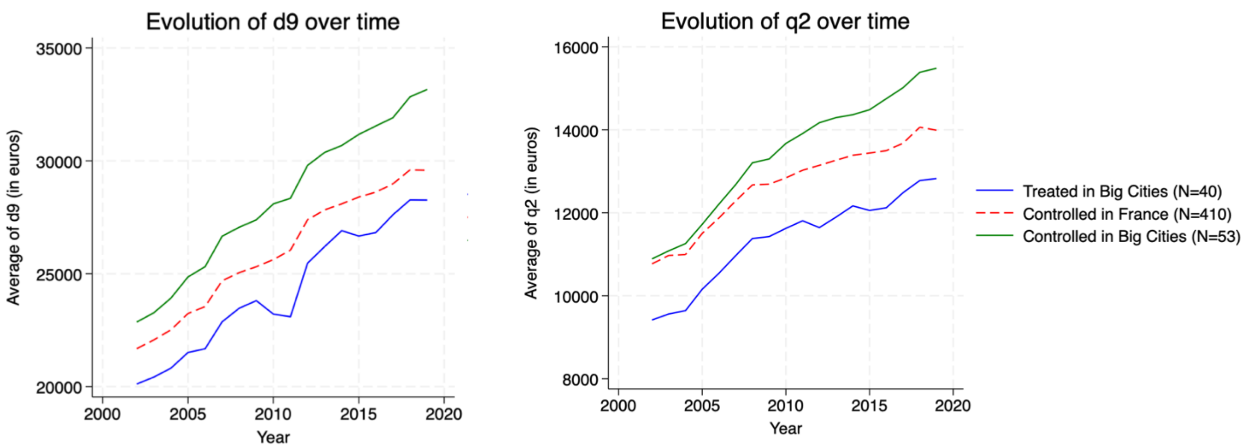


Graph 3.4 Causal impacts of the PNRU on the median income per consumption unit using the classification (CSDID estimator)

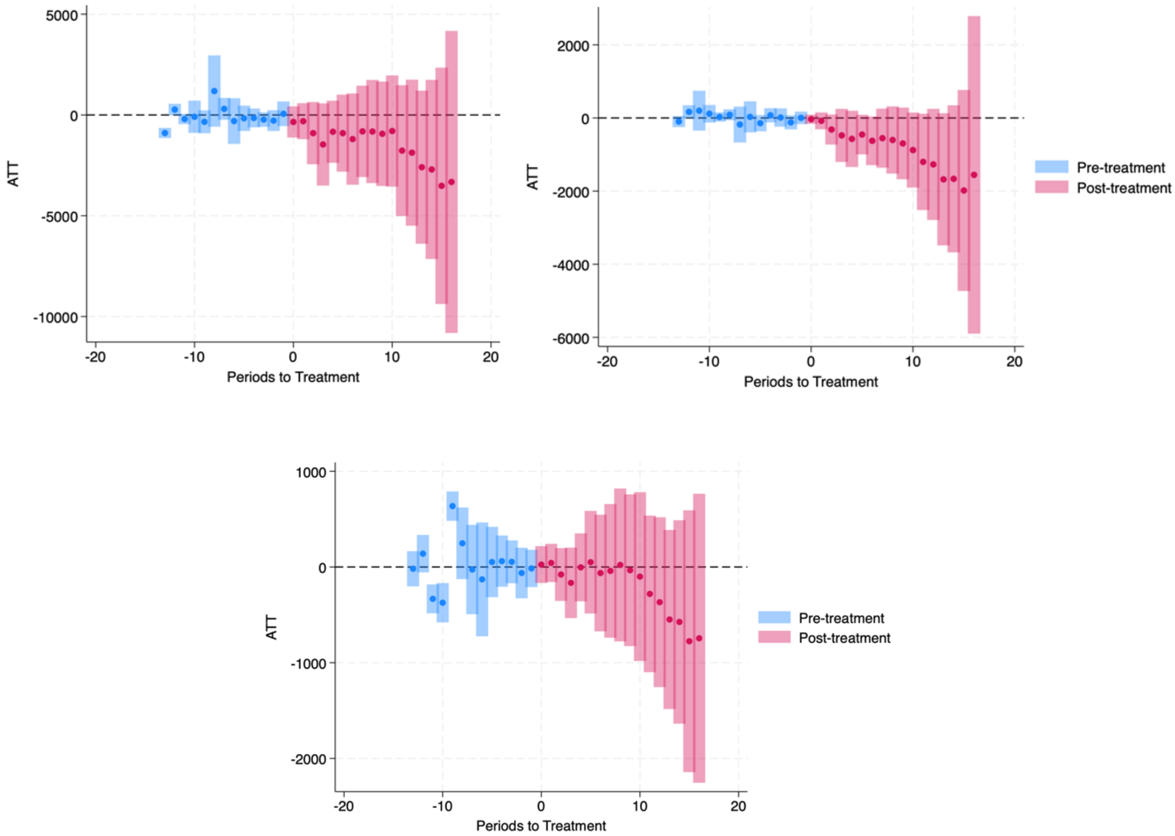



Footnote: Low intensive group (Group 1 top left), intensive rehabilitated and residentialised neighborhoods (Group 2 top right), and highly demolished and reconstructed neighborhoods (Group 3, bottom) using the classification

Graph 4.1 Evolutions of the median and last decile in treated and control neighborhoods



Graph 4.2 Causal impacts of the PNRU on the last decile, median income, and first decile per consumption unit using the classification (CSDID estimator)




Footnote: regression on the last decile is shown at top left, on median income at top right and on the first decile at the bottom

## Public Policy Master's Thesis Series

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# Evaluating Urban Renewal Policies: The Impacts of the PNRU Program on the Distribution of Income within Deprived Neighborhoods in France

Bertille, KEROUAULT

## Abstract

This study evaluates the causal impact of the PNRU (National Urban Renewal Program) law on income distribution in deprived neighborhoods undergoing PNRU operations. Relying on a standard two-ways-fixed-effects and the Callaway and Sant Anna (2021) estimator, I assess the policy's effect on income distribution. My findings reveal a small but statistically significant reduction in income inequality in the short run, with the Gini coefficient decreasing by 0.007 from a baseline of 0.365, on average, post-treatment. This effect is mostly attributed to temporary departures caused by the program but remains robust after accounting for variations in treatment effects. Particularly noteworthy is the pronounced and persistent impact in the upper third of extensively demolished and reconstructed neighborhoods, where the decline in the Gini coefficient is threefold. Additionally, global treatment effects show an increase in income at the first decile, accompanied by decreases in median and last decile incomes per consumption unit, indicating a narrowing of income distribution within neighborhoods. The neighborhood classification specifies the direction of the narrowing and reveals a shift in income values towards central values in heavily renovated neighborhoods, driven by the departure of both the poorest and wealthiest residents. Conversely, low-renovated neighborhoods experience a decline in median income, indicating overall impoverishment, mainly due to the departure of affluent households. Furthermore, the PNRU has effectively reduced poverty within renovated neighborhoods in major cities compared to non-renovated ones, with less gentrification observed in these renovated units compared to neighborhoods solely located in major cities.

## Key words

Urban Renewal Policy, Deprived Neighborhoods, Income Distribution