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Urban Renewal and Displacement of Incumbent Residents: Evidence from Helsinki*

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Abstract

We analyze displacement effects of a recent urban renewal program in Helsinki using population-wide register data and a difference-in-differences design. The data allow us to identify the incumbent residents in the program area and follow their later migration trajectories annually. We find that quality-adjusted housing prices increased in the targeted area by some 10–15% compared to control neighborhoods and that the program attracted higher income residents into new buildings built during the program's implementation. Incumbent public housing tenants and homeowners are more likely to stay in the targeted neighborhood after the program. We do not find evidence of displacement of incumbent tenants in market-rate rental housing. However, these results quite imprecise. These findings suggest that the program was successful in improving neighborhood quality and that incumbent public housing tenants and homeowners benefited from the program.

JEL classification: I38, H31, R23, R28
Keywords: *Place-based policy, residential displacement, urban renewal.*

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1 Introduction

Geographic concentration of poverty is seen as a major problem in many cities throughout the world. This has led local governments to undertake various urban renewal and revitalization programs geared toward deprived neighborhoods. The goal of these programs is to help the residents of these neighborhoods through private and public investments in local amenities and by attracting more affluent residents to the area. However, if the renewal program is successful in improving the quality of the neighborhood, it may lead to increases in housing costs and to displacement of incumbent residents. Thus, to fully understand the welfare implications of urban renewal programs, it is crucially important to understand what happens to incumbent residents of neighborhoods that undergo urban renewal (see Chyn and Katz 2021 and Balboni et al. 2021).

In this paper, we analyze a recent urban renewal program in Helsinki using Finnish population-wide register data that include information on the exact end-of-year residential location (building coordinates) and housing unit for all households. The data allow us to identify the incumbent residents in the program area and follow their later migration trajectories annually. We focus on a single neighborhood in eastern Helsinki, Myllypuro, which was subject to a major renewal program that started in 2009. We use a difference-in-differences (DID) research design where we compare the moving behavior of incumbent residents in the targeted area to the moving behavior of incumbent residents in other similar eastern Helsinki neighborhoods that were not targeted by the program. We analyze separately tenants in market-rate rental housing, tenants in rent-controlled public housing and homeowners. These groups are likely to react differently to changes in neighborhood quality because their housing costs and housing wealth are likely to react differently to neighborhood improvements. Our data span four years before program implementation and nine years after.

Our findings can be summarized as follows. First, we find that quality-adjusted housing prices increased in the targeted area by about 10–15% compared to control neighborhoods. This result is found using only housing units built before the program and despite a fairly sizable increase in the housing stock due to infill development in the targeted area. Second, the program was successful in attracting higher income residents into new buildings built during the program's implementation, leading to a more socially balanced neighborhood.

Third, incumbent residents are more likely to *stay* in the targeted neighborhood compared to incumbent residents in the control neighborhoods. Subsample analysis reveals that this result is driven by public housing tenants and homeowners. Rents in public housing units are regulated to be cost-based, so they cannot reflect changes in demand conditions. These findings suggest that the renewal program was successful in improving neighborhood quality and that incumbent public housing tenants and homeowners benefited from the program because they were protected from increases in housing costs. Finally, we find no evidence of displacement of incumbent tenants in market-rate rental housing. At the same time, we do not observe that these tenants would be more likely to stay in the targeted neighborhood after the program. This suggests that incumbent tenants in market-rate rental housing are willing to pay for the improved quality of the neighborhood (see Vigdor 2010). This is only indirect evidence, because we do not have data on the development of free-market rents. This result comes with the caveat that, if we use cluster-robust methods (Donald and Lang 2007), the estimates concerning market-rate tenants become very imprecise due to the small number of clusters.

We contribute to the literature on the effects of urban renewal and revitalization programs and neighborhood change more generally. This literature has looked at the effects of renewal programs on various outcomes, such as house prices (*e.g.* Rossi-Hansberg et al. 2010, Ahlfeldt et al. 2017, Diamond and McQuade 2019, Koster and van Ommeren 2019, Chareyron et al. 2022, Blanco 2023 and Blanco and Neri 2023), neighborhood level crimes rates (*e.g.* Aliprantis and Hartley 2015, Sandler 2017, Spader et al. 2016, Alonso et al. 2019 and Borbely and Rossi 2023) and neighborhood ethnic and socio-economic mix (*e.g.* González-Pampillón et al. 2020, Neri 2024 and Staiger et al. 2024).[1] Less is known, however, about the effects on incumbent residents in the targeted neighborhoods. Our contribution to the literature comes from using geocoded register data, which allow us to identify all incumbent residents and their tenure status, and follow their residential trajectories for an extensive time period after the renewal program.

Our paper is closest to recent papers by Staiger et al. (2024) and Brunåker et al. (2024) who are also able to use administrative data. Staiger et al. (2024) find that the poverty rate declined in neighborhoods targeted by the HOPE VI revitalization program in the US. However, they also find that incumbent public housing tenants in these neighborhoods did not benefit from this reduction in the poverty rate because they largely moved away from these neighborhoods. They argue that displacement, *i.e.* involuntary moves, was not the main cause of this. Rather, this is mostly due to

[1]Some papers have studied the effects of building demolitions in poor neighborhoods on the residents who were forced to relocate. See e.g. Chyn (2018) and Haltiwanger et al. (2024)

low-income tenants being mobile anyway. They also find that new public housings tenants moving into the targeted neighborhood benefited from improved neighborhood quality. Brunåker et al. (2024) use Swedish population-wide register data and analyze the displacement effects of new large-scale housing construction. They find that the new housing supply gentrified the affected neighborhoods, but did not cause displacement of the incumbent residents. One reason for this finding could be the Swedish rent control policy, which means that housing costs of incumbent tenants cannot reflect changes in the housing demand in the neighborhood.

The remainder of the paper is organized as follows. In Section 2, we introduce the details of the renewal program. In Section 3, we present our data and research design. Section 4 presents our results, and Section 5 concludes.

2 Urban renewal program

We focus our analysis on a major urban renewal program undertaken in the Myllypuro neighborhood in eastern Helsinki (see Figure 1). The neighborhood was mostly built in the 1960s. Almost half of the new housing units were rent-controlled public housing, resulting in a large share of low-income residents in the neighborhood.[2] The area continued to grow into the 1970s, but construction slowed considerably during the 1980s and 1990s. The original Myllypuro shopping center was built in 1966 and became a focal point of the neighborhood. In 1986, the Helsinki subway was extended to Myllypuro and it became better connected to the city center. The subway station was located next to the shopping center.

Some neighborhood improvement projects were undertaken already in the late 1990s due to wear and tear in the housing stock. In addition, various improvements, such as redesigning pedestrian pathways and upgrading local green spaces, were made to enhance the appeal of the neighborhood. The most intense period of renewal in Myllypuro began with the demolition of the old, worn-down shopping center. Construction of the new shopping center began in 2009 and was completed in 2012. New residential housing was built around and on top of it, substantially increasing the housing stock. Due to the large share of public housing in the old housing stock, the redevelopment included hardly any public rental housing with the goal of attracting

[2]The public housing units are subject to rent and tenant-selection regulation. The rents are cost-based and depend on the capital and maintenance costs of the building and do not depend on the characteristics of the tenant. Importantly, rents cannot change due to changes in local housing demand conditions. See Eerola and Saarimaa (2018) for more details.

more affluent residents to the area (see Lilius and Hirvonen 2023 for more details). In addition, new single-family housing was built on the outskirts of the area with the aim of attracting families with children to the catchment area of the local school. An additional boost came in the form of public investments, such as a new municipal health care station and a university of applied sciences campus. We focus on the renewal that began in 2009 in our analysis.

3 Data and research design

3.1 Data

We use data from two sources. First, we utilize micro-level housing transaction data provided by the Finnish Federation of Real Estate Agency. In addition to the transaction price of the housing unit, the data include a rich set of information on the characteristics of the unit and its coordinates. As our purpose is to use housing prices to indirectly measure changes in neighborhood quality, we only use transactions in buildings that were built before program implementation. This ensures that our estimates do not capture the higher quality of newly constructed units. Descriptive statistics on the housing transaction data can be found in Table A1 in the Online Appendix. Unfortunately, we do not have data on rents, which would be useful in analyzing whether the housing costs of tenants increase as a result of the program.

Second, we use population-wide register data provided by Statistics Finland. The data include a rich set of demographic and socio-economic characteristics of individuals, such as age, gender, income, education, and number of children. Importantly, the data also include information on the exact end-of-year residential location (building coordinates) and the housing unit for all households.[3] The data allow us to identify the incumbent residents in the program area and follow their later migration trajectories annually. We analyze separately three household groups: tenants in market-rate rental housing, tenants in rent-controlled public housing, and homeowners.

[3]The granularity of residential location data depends on the number of households in a given spatial unit. We observe building coordinates if there are at least three households living in the building at the end of the year. All households in our main analysis live in multi-story apartment buildings so we observe building coordinates for all of them.

3.2 Research design

We use a difference-in-differences (DID) design in which we compare the development of housing prices or the moving behavior of incumbent residents in the targeted area with those in other similar neighborhoods that were not targeted by the program. The treated neighborhood Myllypuro is shown in blue, and the control neighborhoods Puotila, Rastila and Mellunmäki in yellow on the map in Figure 1. The control neighborhoods are similar to the treated neighborhood in that they are all located along the subway line in eastern Helsinki and have a similar socio-economic structure.

Our sample consists of apartments and residents in multistory buildings within a 600 meter radius from the respective neighborhood shopping centers, as shown on the map. The analysis period is 2005–2017, which we divide into three periods: pre-program period (2005–2008), implementation period (2009–2012) and post-program period (2013–2017).

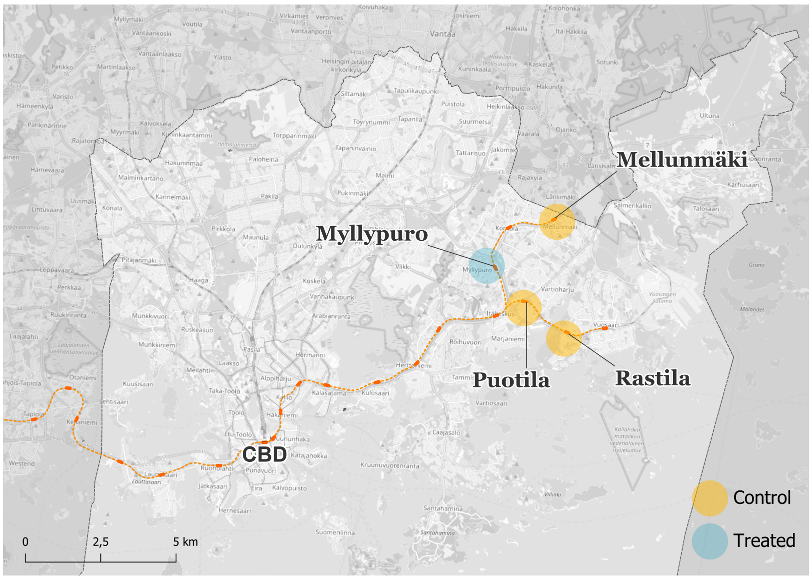


Figure 1: Treatment and control neighborhoods.

Notes: The map displays the treated neighborhood Myllypuro (blue) and control neighborhoods (yellow). A ring with a radius of 600 meters is formed around the shopping center in each neighborhood. Subway line and stations are displayed in orange. Dashed line is Helsinki municipality boundary.

To get a sense of what happened to neighborhood quality, we start by estimating the effects of the program on housing prices employing the following dynamic DID specification using repeated cross-sectional data:

$$p_{it} = \sum_{\substack{s=2005 \\ s\neq 2008}}^{2017} \delta_s \mathbb{1}_{\{s=t\}} \mathbb{1}_{\{treated_i=1\}} + x_{it}\beta + \theta_t + u_{it}, \tag{1}$$

where p_{it} is the log transaction price of unit i sold in year t. $\mathbb{1}_{\{s=t\}}$ denotes an indicator function that takes value one for a specific year and is zero otherwise. The last year before the program started, 2008, is the omitted category. Likewise, $\mathbb{1}_{\{treated_i=1\}}$ is an indicator function that denotes the treatment area. We control for unit characteristics (x_{it}) reported in Table A1 in the Online Appendix and sale year fixed effects (θ_t).

Next, we turn to analyzing the displacement of incumbent residents. Incumbent residents are defined as those individuals who lived in the neighborhood in a multi-story building at the end of 2008, that is, before the construction of the new center block began. We also limit our sample to households where the head of the household was at least 22 years old and not a full-time student. We then follow this group of incumbent residents in the treated and control neighborhoods until the end of 2017. Following Diamond et al. (2019), we specify a dynamic DID model:

$$y_{it} = \sum_{\substack{s=2005 \\ s\neq 2008}}^{2017} \delta_s \mathbb{1}_{\{s=t\}} \mathbb{1}_{\{treated_i=1\}} + \alpha_i + \theta_t + u_{it}, \tag{2}$$

where y_{it} is a dummy variable, which is equal to one if individual i in year t still lives in the same neighborhood as it did at the end of 2008. For households with more than one member, we include only one individual per household. $\mathbb{1}_{\{s=t\}}$ and $\mathbb{1}_{\{treated_i=1\}}$ are defined as before. Individual fixed effects, α_i, are included to control for any person-specific time-invariant factors that could be correlated with both the treatment and the outcome variable. We also run regressions using a three-period DID specification where the pre-period (2005–2008) is followed by program implementation period (2009–2012), and post-period (2013–2017).

The DID specification produces estimates with a causal interpretation under three assumptions. The first is that in the absence of the renewal program, the out-of-neighborhood mobility of incumbent residents in the program and the control neighborhoods would have developed similarly. This common trends assumption can be tested indirectly by analyzing the pre-treatment trends in the treatment and control groups. The second assumption is that there are no other reforms or events that coincide with the renewal program that affected the treatment and control neighborhoods differently. We are unaware of any such events that occurred during the analysis period, and we have selected the control neighborhoods so that there was no major renewal or infill development in them. Finally, there should be no spillovers between the treatment and control neighborhoods. That is, the mobility of incumbent residents in the control neighborhoods is not affected by the mobility decisions of incumbent residents in the treatment neighborhood. Although in principle whenever the moving behavior of some group changes it affects the options of the other people in the same housing market (*e.g.* Eerola et al. 2021), we believe that the treatment area is so small compared to the whole Helsinki area housing market that these spillovers are likely to be inconsequential for our analysis.

Statistical inference is challenging because the error terms in our regression models may be correlated within neighborhoods. Since we only have four neighborhoods in total, standard clustering techniques do not work in our case (Abadie et al. 2023). To address this issue, we present two sets of results in which standard errors are clustered either at the individual level, allowing for error correlation within individuals, or at the neighborhood level using the two-step method suggested by Donald and Lang (2007) method, allowing for error correlation within neighborhoods. This amounts to using individual-level data to estimate neighborhood-year fixed effects in the first step (while controlling for individual level fixed effects) and then using these neighborhood-year fixed effects as data in a DID analysis in the second step. The second step effectively treats the number of neighborhood-years as the number of observations in the DID analysis (48 in our case).

We analyze separately the moving behavior of tenants in market-rate rental housing, tenants in rent-controlled public housing, and homeowners. The main difference between the two tenant groups is that market rents can react to changes in neighborhood attractiveness and housing demand, while the rents in public housing units are cost-based (regulated and monitored) and should not react to changes in demand. For homeowners, improved neighborhood quality can translate into higher housing wealth, which may also affect their moving behavior.

Descriptive statistics for these household groups in the treatment and control neighborhoods at the end of 2008 are presented in Table 1. The households in the targeted neighborhood have somewhat lower incomes, lower education level, and are on average older than the households in the control neighborhoods. This is true for all tenure-status groups.

Table 1: Descriptive statistics for households in 2008.

	All		Market-rate		Public housing		Homeowners	
	Control	Treated	Control	Treated	Control	Treated	Control	Treated
Income (TEUR)	18.06	16.36	16.01	14.50	15.19	14.52	20.44	18.39
Age	50.64	55.09	43.40	46.56	46.92	52.26	55.29	59.96
Female	0.42	0.41	0.42	0.33	0.41	0.43	0.42	0.42
University degree	0.26	0.20	0.23	0.19	0.14	0.09	0.34	0.29
Employed	0.58	0.46	0.64	0.51	0.54	0.46	0.58	0.45
Unemployed	0.08	0.08	0.11	0.14	0.14	0.13	0.03	0.03
Family with children	0.26	0.19	0.21	0.11	0.37	0.27	0.21	0.15
Floor area (m^2)	60.34	60.49	51.89	53.65	61.67	58.70	62.45	64.01
Dist. to mall (m)	370	360	360	390	360	340	380	360
N	8061	2311	1426	340	2454	870	4181	1101

Notes: The sample includes residents within a 600 meter radius of the neighborhood shopping center. Disposable income is calculated by dividing the total household income by the number of household members. The remaining statistics relate to either the characteristics of the household head or the attributes of the housing unit.

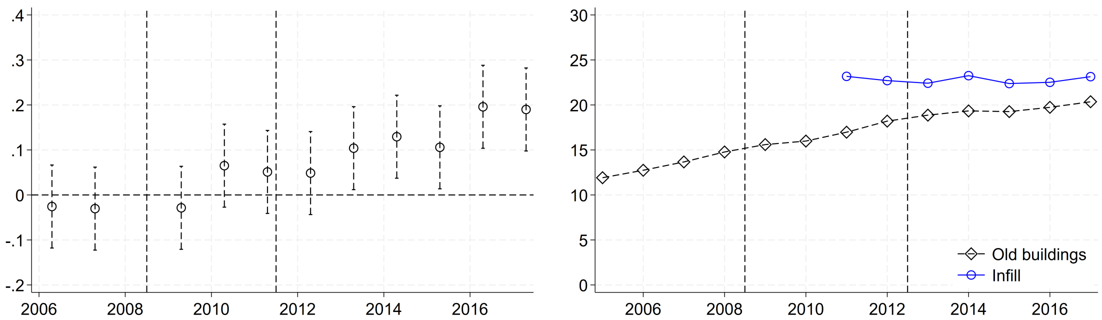
4 Results

4.1 Housing prices and neighborhood change

We start by analyzing what happens to neighborhood quality and residential composition. We measure neighborhood quality indirectly using housing prices. Figure 2a plots the yearly average treatment effects of our dynamic DID specification, controlling for housing unit characteristics following Eq. (1). Before the implementation of the program, prices developed in a similar way in all neighborhoods, supporting the assumption of common trends. Prices started to increase more in the treated neighborhood starting in 2010 during program implementation. Another price increase is evident after program implementation in 2013–2017. By 2016 and 2017, prices increased by some 15% more in the treated neighborhood compared to the control neighborhoods. These findings suggest that the renewal program was successful in improving the quality of the neighborhood.[4]

[4]Figure A1 in the Online Appendix shows the development of housing prices per square meter in the treated and control neighborhoods. These price trends reveal the same pattern as the DID estimates. Table A2 in turn presents results from DID specification with one pre-treatment and two

Figure 2b shows the development of mean disposable income for households living in multistory buildings within 600 meters of the shopping center. These are shown separately for residents of old buildings (built before 2009) and new buildings (built during and after program implementation). The households in the new buildings have clearly higher incomes on average than their counterparts in the old housing stock. This means that the program was successful in attracting higher income residents to the area, leading to a more socially balanced neighborhood.



(a) Housing prices – DID estimates

(b) Disposable income (TEUR) in treatment area

Figure 2: Housing prices and neighborhood change.

Notes: Panel (a) plots dynamic DID estimates with 95% confidence intervals estimated using the two-step Donald and Lang (2007) method. The dependent variable is the log of transaction price. The model controls for housing unit characteristics reported in Table A1 in the Online Appendix. The number of observations is 2867. Panel (b) plots mean disposable income (TEUR) of residents in old and new housing stock in the program area. The vertical lines distinguish pre-program period, implementation period and post-program period.

4.2 Residential displacement

Figure 3 shows our dynamic DID estimation results with respect to displacement. We report results for all incumbent residents (Figure 3a) and separately for market-rate tenants (Figures 3b), public housing tenants (Figures 3c) and homeowners (Figures 3d). The pre-treatment trends leading up to program implementation (year 2009) are very similar between the treatment and the control group. This is true for all incumbent residents (Figure 3a) and for the tenure subgroups separately (Figures 3b–3d). This lends support for the common trends assumption, which is crucial for

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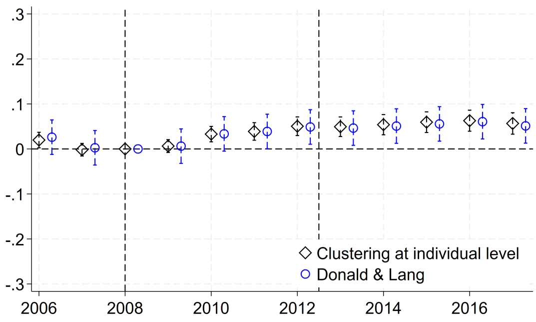
post-treatment periods. Again, the results echo the results in Figure 2a.

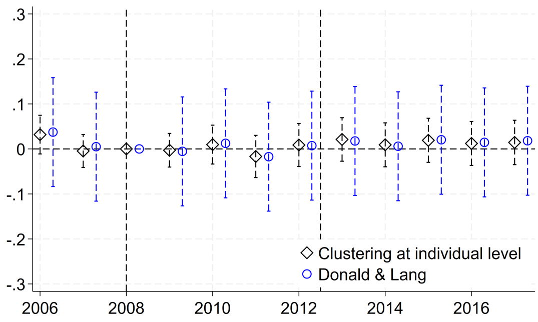
the causal interpretation of the results.[5]

After the implementation of the program began, incumbent residents are more likely to stay in the targeted neighborhood compared to incumbent residents in the control neighborhoods (Figure 3a). However, there are interesting differences between different housing tenure groups. Based on the point estimates, market-rate tenants are no more likely to stay or leave the targeted neighborhood compared to similar tenants in the control neighborhoods (Figure 3b). The point estimates are fairly close to zero, but imprecisely estimated. This is true especially if we use the two-step Donald and Lang (2007) method. Thus, based on the confidence intervals, we cannot rule out displacement effects. Public housing tenants in the targeted neighborhood, on the other hand, are clearly more likely to persistently stay in the same neighborhood compared to their counterparts in the control neighborhoods (Figures 3c). This difference arises already during the implementation phase and increases further after the program implementation. A similar pattern is evident for homeowners, although the effect is smaller (Figure 3d). Incumbent homeowners are more likely to stay in the targeted neighborhood compared to the incumbent homeowners in the control neighborhoods. However, the yearly point estimates for homeowners are not statistically significantly different from zero if we use the two-step Donald and Lang (2007) method.

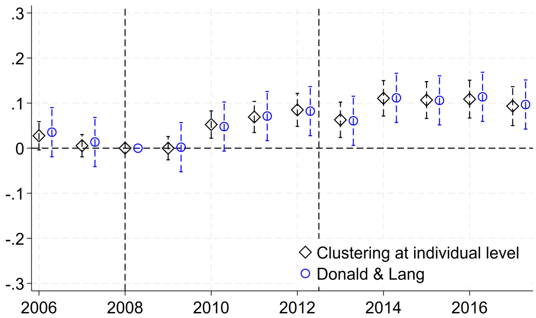
[5]For transparency, we report descriptive graphs that illustrate how likely incumbent residents are to stay in their 2008 neighborhood in Figure A2 in the Online Appendix. These results are very much in line with the dynamic DID estimates in Figure 3.



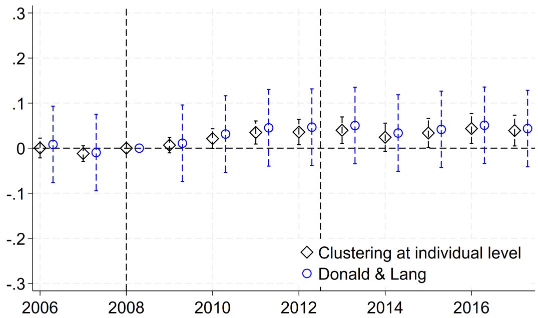
(a) All



(b) Market-rate tenants



(c) Public housing tenants



(d) Homeowners

Figure 3: Probability to stay in the same neighborhood - dynamic DID estimates.

Notes: The figure plots dynamic DID estimates with 95% confidence intervals. Confidence intervals are based on standard errors clustered at the individual level and using the two-step Donald and Lang (2007) method. The vertical lines distinguish pre-program period, implementation period and post-program period. The number of observations in panels are (a) 125,170, (b) 32,977, (c) 33,326 and (d) 58,879.

To get a better sense of the magnitude of these effects and to gain more degrees of freedom for the second step of the Donald and Lang (2007) method, we present the estimation results of our three-period DID model along with pre-treatment baselines for the outcome variable in Table 2. The results from Table 2 are largely in line with Figure 3. The results for market-rate tenants and homeowners are more precicely estimated when using the two-step Donald and Lang (2007) method. However, the estimates for market-rate housing are still quite imprecise and we cannot rule out moderate displacement effects. For homeowners, the point estimate for the post-treatment period is now statistically significant both when clustering at individual and neighborhood level. The treatment effect after program implementation is roughly 8% for public housing tenants and roughly 4% for homeowners. In other words, public housing tenants (homeowners) in the treatment neighborhood are 8% (4%) more likely to still live in the neighborhood after program implementation compared to a public housing tenants (homeowners) in the control neighborhood. When considering the pre-treatment means of the outcome, the treatment effect is indeed larger for public housing tenants than for homeowners.

To sum up, the results imply that public housing tenants benefited from the renewal program as they can enjoy a higher quality neighborhood without experiencing increases in their housing costs. For homeowners, in addition to improved neighborhood quality, the renewal program led to a positive wealth shock. In principle, this positive wealth shock could allow them to move to higher quality neighborhoods which they were unwilling to pay for before. However, the results indicate that homeowners stay longer in the targeted neighborhood, suggesting that they value the improvements in the neighborhood.

Table 2: Probability to stay in the same neighborhood.

	(1) All	(2) Market-rate	(3) Public housing	(4) Homeowners
Panel A: Clustering at individual level				
Treated × 2009–2012	0.027***	-0.008	0.040***	0.029***
	(0.008)	(0.020)	(0.014)	(0.011)
Treated × 2013–2017	0.051***	0.007	0.086***	0.041***
	(0.011)	(0.024)	(0.019)	(0.015)
Pre-period mean control	0.90	0.84	0.91	0.94
Pre-period mean treated	0.91	0.84	0.92	0.93
N	125,170	32,977	33,326	58,879
Panel B: Two-step Donald and Lang (2007)				
Treated × 2009–2012	0.022**	-0.015	0.035**	0.034*
	(0.010)	(0.027)	(0.016)	(0.019)
Treated × 2013–2017	0.043***	0.001	0.081***	0.044**
	(0.010)	(0.026)	(0.016)	(0.019)
Pre-period mean control	0.90	0.84	0.91	0.94
Pre-period mean treated	0.91	0.84	0.92	0.93
N	125,170	32,977	33,326	58,879

Notes: The figure reports estimates from DID models with one pre- and two post-treatment periods. Standard errors are reported in the parentheses and are clustered at the individual level in panel A and using the two-step Donald and Lang (2007) method in panel B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also run sensitivity checks related to how we define neighborhoods and who we define as incumbent residents. Starting with the neighborhood definition, the choice of a radius of 600 meters from the focal point of the neighborhood is, of course, somewhat *ad hoc*. Figure A3 and Table A3 in the Online Appendix present results where the radius is extended to 800 meters. The results are very similar to those that use the smaller cut-off radius (Figure 3 and Table 2). Using an even larger radius would run the risk of including residents who actually live in another neighborhood and are not affected by the program.

In our main analysis, we define incumbent residents as those who lived in their respective neighborhoods at the end of 2008. A potential problem with this choice is that some of these people may have just moved into the program neighborhood with a plan to stay there longer because they knew about the program and were anticipating improvements in neighborhood quality. To alleviate this concern, we define incumbent residents as those who lived in their respective neighborhoods at the end of 2007 and 2008. The results using this alternative definition are presented in Figure A4 and Table A4 in the Online Appendix. Again, the results are very similar to the results in our main specification in Figure 3 and Table 2.

5 Conclusions

In this paper, we analyze the effects of an urban renewal program in Helsinki using a difference-in-differences research design. Our main interest lies in the program's effect on incumbent residents who may be displaced from the neighborhood. Our analysis draws on rich population-wide register data, allowing us to follow incumbent residents and to disentangle effects based on the residents' housing tenure status.

We find that the program improved neighborhood quality. Housing prices increased substantially in the housing stock built prior to program implementation in the program area compared to the control areas. We also find that new infill development attracted higher income households to the targeted area, leading to a more socially balanced neighborhood. We do not find evidence of displacement. Tenants in market-rate rental housing are no more or less likely to leave the targeted neighborhood, although these estimates are quite imprecise. Tenants in rent-controlled public housing and homeowners, on the other hand, are more likely to stay in the targeted neighborhood.

These results imply that urban renewal programs can be particularly effective in helping low-income incumbent residents when they target neighborhoods with large shares of rent-controlled public housing or in cities with rent control. On the other hand, as incumbent residents are less likely to move away from the targeted neighborhood, people who would have moved into the area in the absence of the program are now unable to do so. This group was potentially negatively affected by the program. Naturally, we cannot observe these individuals in our data, and addressing this question is beyond the scope of this paper.

Two additional considerations are worth pointing out. First, the fact that house prices increased together with our results concerning incumbent homeowners and public housing tenants imply that new home buyers, incumbent homeowners, and low-income public housing tenants value the same aspects of neighborhood quality improvements (see *e.g.* Almagro and Domínguez-Iino 2024, Almagro et al. 2024 and Couture et al. 2024). Second, our results imply that neighborhood turnover decreased as a result of the program, which may be another benefit of neighborhood improvement. For example, Gibbons et al. (2017) find that the educational progress of teenagers in the UK was reduced by the high turnover of neighbors of similar age.

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Online Appendix: Additional results

Table A1: Descriptive statistics for housing transaction data in estimation sample.

	Treated		Control	
	Mean	SE	Mean	SE
Transaction price (kEUR)	136.9	33.7	145.2	35.3
Living area (m^2)	62	16.4	58	17.6
Maintenance cost (EUR/month)	238	65	241	76
Building age (years)	45.7	4.5	39.1	12.2
Floors in building	5.6	1.5	3.4	1.0
Floor number	3.6	1.8	2.2	1.1
Number of rooms	2.6	0.8	2.4	0.9
Lift (0/1)	0.7	0.5	0.2	0.4
Balcony (0/1)	0.6	0.5	0.5	0.5
Distance to shopping center (m)	333	125	367	146
N	607		2260	

Notes: Sample consists of multistory housing transactions in treatment and control areas. Only buildings built before program implementation are considered.

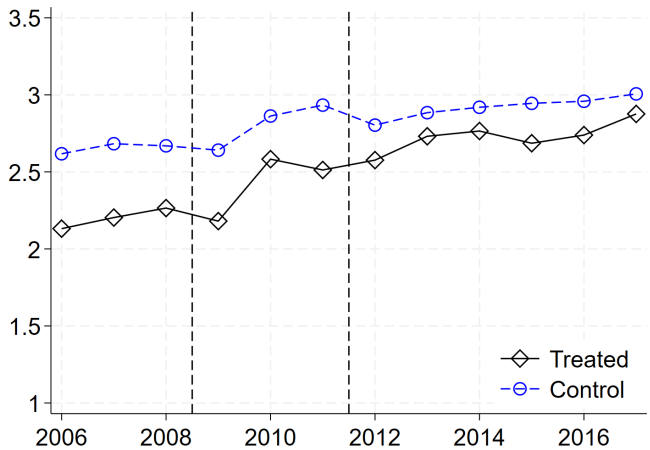
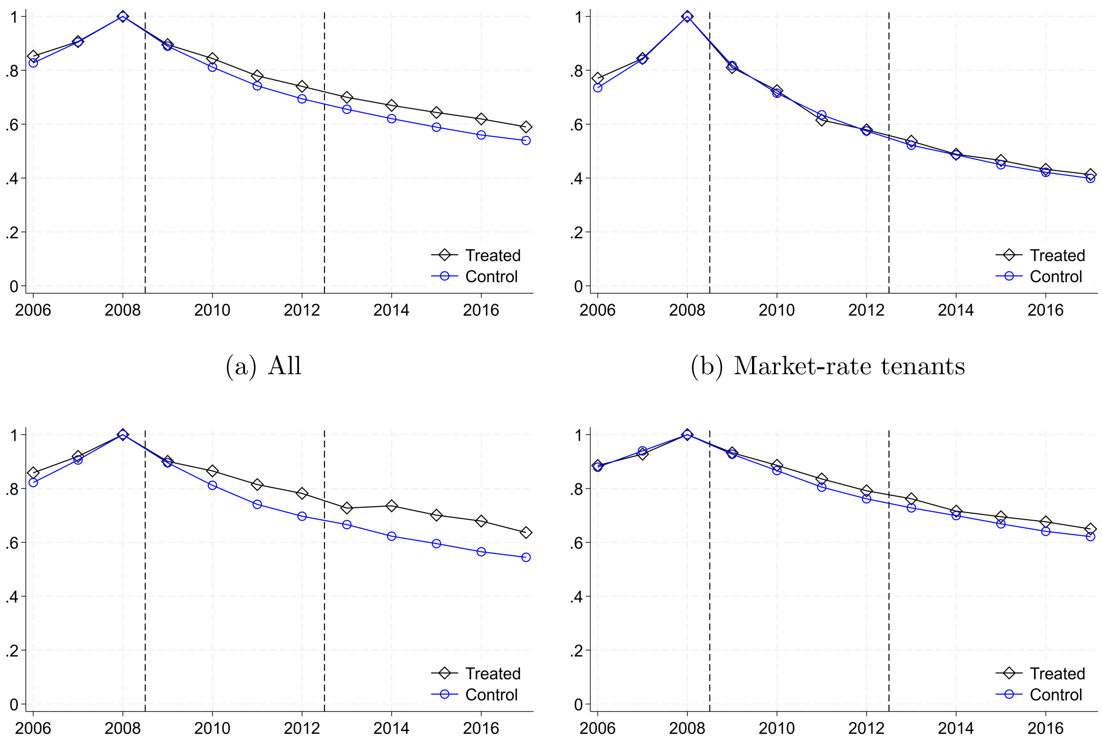


Figure A1: Mean housing prices in treatment and control neighborhoods (EUR/m^2).

Table A2: Effect on housing prices.

Treated × 2009–2012	0.053*
	(0.026)
Treated × 2013–2017	0.164***
	(0.025)
Pre-period mean control	151,200
Pre-period mean treated	133,800
N	2867

Notes: The figure reports estimates from a DID model with one pre- and two post-treatment periods estimated using the two-step Donald and Lang (2007) method. The dependent variable is the lof of transaction price. Standard errors are reported in the parentheses. The DID model control for housing characteristics reported in Table A1 in the Online Appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



(a) All

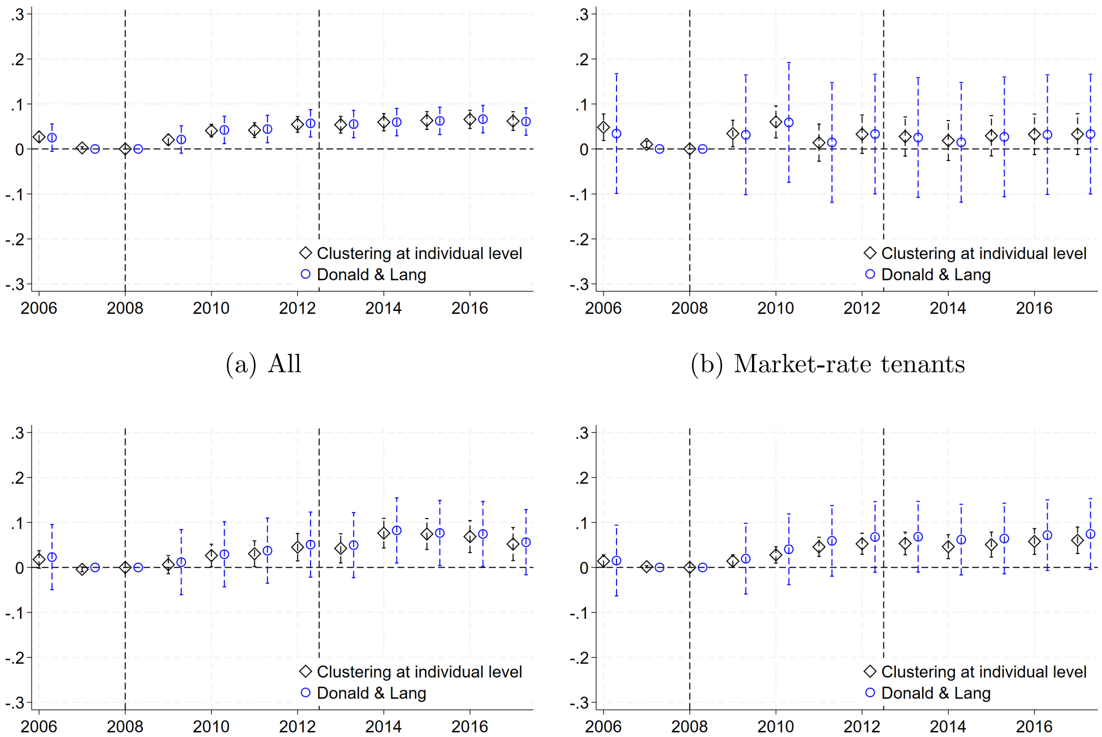
(b) Market-rate tenants

(c) Public housing tenants

(d) Homeowners

Figure A2: Probability to stay in the same neighborhood as in 2008 - descriptive.

Notes: The figure plots the share of residents who still live in the same area as in 2008. The vertical lines distinguish pre-program period, implementation period and post-program period. The number of observations in panels are (a) 125,170, (b) 32,977, (c) 33,326 and (d) 58,879.



(a) All

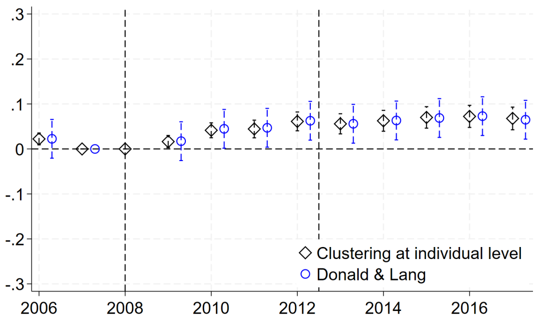
(b) Market-rate tenants

(c) Public housing tenants

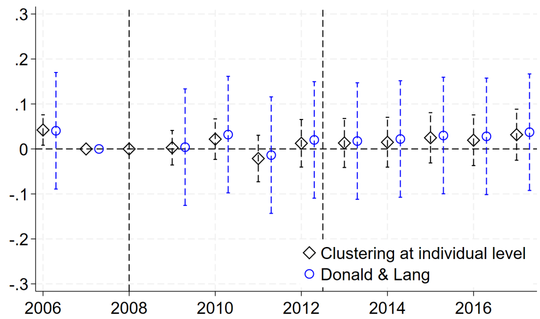
(d) Homeowners

Figure A3: Treatment effect with alternative definition of neighborhoods – 800 meter radius.

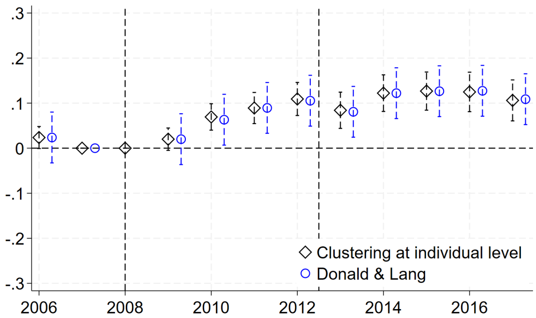
Notes: The figure plots DID estimates with 95% confidence intervals. Confidence intervals are based on standard errors clustered at the individual level and using the two-step Donald and Lang (2007) method. The vertical lines distinguish pre-program period, implementation period and post-program period. The number of observations in panels are (a) 146,283, (b) 37,344, (c) 42,736 and (d) 66,215.



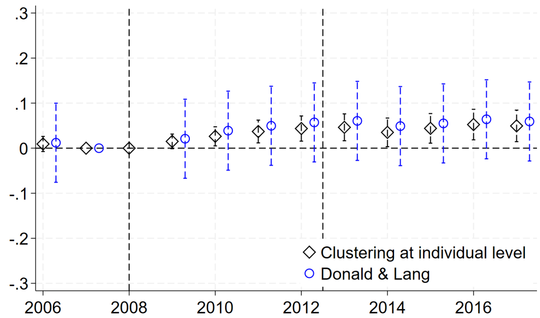
(a) All



(b) Market-rate tenants



(c) Public housing tenants



(d) Homeowners

Figure A4: Treatment effect with alternative definition of incumbent residents –lived in area at the end of 2007 and 2008.

Notes: The figure plots DID estimates with 95% confidence intervals. Confidence intervals are based on standard errors clustered at the individual level and using the two-step Donald and Lang (2007) method. The vertical lines distinguish pre-program period, implementation period and post-program period. The number of observations in panels are (a) 109,506, (b) 26,000, (c) 29,009 and (d) 54,509.

Table A3: Probability to stay in the same neighborhood – 800m radius

	(1) All	(2) Market-rate	(3) Public housing	(4) Homeowners
Panel A: Clustering at individual level				
Treated × 2009–2012	0.030***	0.018	0.022*	0.030***
	(0.007)	(0.016)	(0.011)	(0.009)
Treated × 2013–2017	0.052***	0.010	0.059***	0.049***
	(0.009)	(0.021)	(0.016)	(0.013)
Pre-period mean control	0.90	0.84	0.90	0.94
Pre-period mean treated	0.91	0.85	0.92	0.93
N	146,283	37,344	42,736	66,215
Panel B: Two-step Donald and Lang (2007)				
Treated × 2009–2012	0.033***	0.023	0.025	0.0415**
	(0.008)	(0.030)	(0.017)	(0.018)
Treated × 2013–2017	0.053***	0.015	0.060***	0.063***
	(0.008)	(0.029)	(0.016)	(0.017)
Pre-period mean control	0.90	0.84	0.90	0.94
Pre-period mean treated	0.91	0.85	0.92	0.93
N	146,283	37,344	42,736	66,215

Notes: The table reports estimates from a DID model with one pre- and two post-treatment periods. Standard errors are reported in parentheses and are clustered at the individual level in panel A and using the two-step Donald and Lang (2007) method in panel B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Probability to stay in the same neighborhood – lived in the area at the end of 2007 and 2008.

	(1) All	(2) Market-rate	(3) Public housing	(4) Homeowners
Panel A: Clustering at individual level				
Treated × 2009–2012	0.034***	-0.008	0.064***	0.028***
	(0.008)	(0.020)	(0.014)	(0.010)
Treated × 2013–2017	0.059***	0.008	0.105***	0.043***
	(0.011)	(0.026)	(0.019)	(0.015)
Pre-period mean control	1.00	1.00	1.00	1.00
Pre-period mean treated	1.00	1.00	1.00	1.00
N	109,506	26,000	29,009	54,509
Panel B: Two-step Donald and Lang (2007)				
Treated × 2009–2012	0.035***	-0.003	0.062***	0.038*
	(0.011)	(0.029)	(0.016)	(0.020)
Treated × 2013–2017	0.058***	0.014	0.105***	0.054***
	(0.011)	(0.028)	(0.016)	(0.019)
Pre-period mean control	1.00	1.00	1.00	1.00
Pre-period mean treated	1.00	1.00	1.00	1.00
N	109,506	26,000	29,009	54,509

Notes: The table reports estimates from a DID model with one pre- and two post-treatment periods. Standard errors are reported in parentheses and are clustered at the individual level in panel A and using the two-step Donald and Lang (2007) method in panel B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.