Neighborhoods, Perceived Inequality, and Preferences for Redistribution : Evidence from Barcelona

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Abstract

I study the effects of neighborhoods on perceived inequality and preferences for redistribution. Using administrative data on the universe of dwellings and real estate transactions in Barcelona (Spain), I construct a novel measure of local inequality — the Local Neighborhood Gini (LNG). The LNG is based on the spatial distribution of housing within a city, independent of administrative boundaries, and building-specific. I elicit inequality perceptions and preferences for redistribution from an original large-scale survey conducted in Barcelona. I link those to respondents' specific local environments using exact addresses. I find that a one standard deviation increase in LNG is associated with 4% higher perceived inequality, but with (if anything) *lower* demand for redistribution. Residential sorting explains the counter-intuitive pattern. To causally identify the effects of local environments, I exploit within-neighborhood variation from the rise of new apartment buildings as a quasi-experiment. Exposure to new buildings increases perceived inequality by 7% and demand for redistribution by 1%. Effects come from higher perceived income at the top. Local environments shape inequality perceptions and (to a lesser extent) demand for redistribution.

Keywords: Inequality, Gini, Redistribution, Housing
JEL Codes: D31, D63, O18

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1 Introduction

Perceptions are strong predictors of individual behavior. Individuals that perceive their country as unequal or with low social mobility tend to hold a favorable view towards redistribution (Alesina et al. 2018b, Gimpelson and Treisman 2018). In contrast, those who believe that society is fair, with high social mobility, or with many immigrants, are less willing to redistribute (Alesina et al. 2018a; 2012). Perceptions may be subjective, but they ultimately impact policy.

Local environments are likely to shape perceptions. Our knowledge about the origin of perceptions is still limited, but we know that neighborhoods are critical determinants of a wide variety of outcomes and constitute the physical space in which a relevant share of social interactions take place (Bayer et al. 2008, Chetty et al. 2018, Wellman 1996). It is thus reasonable to expect them to also exert some influence on perceptions, and recent research provides suggestive evidence in favor of this channel (Cruces et al. 2013, Hauser and Norton 2017, Minkoff and Lyons 2019, Xu and Garand 2010).

Local inequality may directly influence beliefs about inequality at a more aggregate level, and therefore also affect preferences for redistribution. However, establishing causality is challenging. Individuals choose where to live, and their views about inequality and redistribution could substantially weigh in their location choices. For example, those with a strong distaste for inequality — which could correlate with redistribution attitudes — may deliberately avoid highly unequal neighborhoods in a city. Consequently, looking at the raw correlation between local environments and perceptions or demand for redistribution could be misleading in the presence of endogenous sorting. In this paper, I exploit a quasi-experimental setting and a rich array of survey and administrative data to study the causal effects of neighborhoods on perceived inequality and preferences for redistribution.

I start by introducing a novel measure of local inequality that captures disparities in dwelling characteristics (e.g., space or value) in the immediate surroundings of a building. I call this measure Local Neighborhood Gini (LNG). The LNG is especially suitable for the present application due to its granularity — which contrasts with the coarseness of standard inequality measures. It could also be an appropriate tool in alternative applications, whenever local environments may be relevant.

I subsequently construct the LNG for Barcelona and a sample of large Spanish cities by combining data from the Spanish Cadastre and administrative data from the Catalan Tax Authority (ATC). The Cadastre data comprises detailed information and the precise geolocation of the universe of real estate in Spain. The ATC data contains records on the universe of real estate transactions in Catalonia from 2009 to 2019, including the price and unique Cadastre identifier for each transaction. Thus, by combining both datasets and applying machine learning methods, I can predict the market value of all dwellings in Barcelona. I then compute the LNG, which assigns a value reflecting the level of local inequality specific to *every* building in my sample.

I conducted an original large-scale online survey in Barcelona to elicit inequality perceptions and demand for redistribution at the national level. To measure perceived inequality, I elicited respondents' perceived national income distribution building from existing questions in the literature (Chambers et al. 2014, Eriksson and Simpson 2012, Hvidberg et al. 2020), and then computed the implied Gini index. I measured demand for redistribution using a question adapted from the General Social Survey (GSS). The question makes respondents face a trade-off between better public services and social benefits on the one hand versus lower taxes on the other. The survey recorded participants' exact addresses, allowing me to link individual responses to my measure of local inequality and other neighborhood characteristics. The survey provides the necessary structure to identify the link between local environments, perceptions, and preferences for redistribution.

Local inequality is positively associated with perceived inequality in narrowly defined neighborhoods. When local neighborhoods are defined as the area within 200 meters of respondents' dwellings, one standard deviation (SD) increase in the LNG translates into a 4% increase in perceived inequality. That association remains positive within 500 meters of respondents' dwellings. The relationship between local inequality and demand for redistribution is negligible. If anything, it is negative. Nevertheless, results also suggest that left-wing individuals are more prone (13.5%) to reside in the least unequal areas of a neighborhood, which calls for some caution in interpreting the previous associations as causal. If there is endogenous sorting on observables, unobservable factors could also play a role.

To get at causality, I exploit quasi-experimental variation within neighborhoods induced by the recent rise of new apartment buildings. Identification hinges on the assumption that individuals who have resided in the area for long enough are unlikely to have sorted into their current locations based on the hypothetical rise of an apartment building in the future.

Survey respondents exposed to a new apartment building are significantly more likely to perceive higher inequality levels (7% more) and somewhat more likely to demand higher redistribution (1.3% more). Results are driven by higher perceived income at the top and are slightly larger among young, low-income, left-wing, and Spanish-born individuals. They are unlikely to be caused by individuals sorting into or displaced by gentrifying neighborhoods, as treatment effects are still present when restricting the attention to homeowners or individuals residing in the same dwelling long before treatment exposure. Results confirm that local environments significantly influence perceived inequality and (to a lesser extent) demand for redistribution.

This paper directly speaks to the literature studying the determinants of perceived inequality. Recent work suggests that individuals perceive more inequality when they are less accepting of preexisting hierarchies in society (Kteily et al. 2017); when they are more exposed to media coverage on inequality-related topics (Diermeier et al. 2017, Kim 2019); or when they live in more unequal environments (Franko 2017, Minkoff and Lyons 2019, Newman et al. 2018, Xu and Garand 2010). The contribution to this strand of research is twofold. First and foremost, this is the first paper to identify a causal link between local environments and inequality perceptions. In the past, research has documented associations between perceptions and neighborhood characteristics. Albeit suggestive, they could not be strictly interpreted as causal.[1] Secondly, the paper also attempts

[1]For example, in Buenos Aires, Cruces et al. (2013) showed that perceived income rank at the national level was

to characterize the "relevant" spatial scope of local environments by inspecting the aggregation level in which perceived and actual inequality are most highly correlated. In line with Sands and de Kadt (2019), descriptive and quasi-experimental results suggest that the "relevant" local neighborhood is narrow.

Secondly, this paper contributes to the well-established literature studying the connection between perceptions and preferences for redistribution. The original focus in this literature was on mobility perceptions — also referred to as prospects for upward mobility (POUM) (Benabou and Ok 2001, Piketty 1995). In recent years, there has been a significant widening in the array of objects studied as potential drivers. Among others, these include perceptions on immigration (Alesina et al. 2018a; 2021), social mobility (Alesina et al. 2018b), relative income (Cruces et al. 2013, Fernández-Albertos and Kuo 2018, Fisman et al. 2021, Hoy and Mager 2021, Hvidberg et al. 2020, Karadja et al. 2017), fairness (Alesina and Angeletos 2005, Alesina et al. 2012), and inequality (Engelhardt and Wagener 2014, Gimpelson and Treisman 2018, Niehues 2014). The contribution is on three fronts. First, the paper provides evidence on the causal link between local environments and preferences for redistribution. As in Sands and de Kadt (2019), but in contrast with Sands (2017), the relationship appears to be overall weak.[2] Second, the quasi-experimental approach followed in identification — more usual in urban economics (Autor et al. 2014, Chyn 2018, Diamond and McQuade 2019) — represents a methodological departure from what is common in the distributional preferences literature, which typically exploits variation generated in surveys or lab experiments. Finally, the quasi-experimental setting allows me to study the causal effects on actual electoral outcomes, in addition to standard survey proxies of demand for redistribution.

Finally, this paper contributes to the literature on the measurement of inequality. This research is primarily descriptive and typically combines a wide variety of sources — such as survey and administrative data — to produce estimates of inequality, usually at the country level, over long time horizons, and with a strong focus on cross-country comparability (Alvaredo and Saez 2009, Blanco et al. 2018, Fuchs-Schündeln et al. 2010, Martínez-Toledano 2020, Piketty and Saez 2003; 2006; 2014). In recent years, the attention has partly shifted towards a more local measurement of inequality, with a particular emphasis on cities (Fogli and Guerrieri 2019, Glaeser et al. 2009). The reason for the shift is likely a combination of the increased availability of high-quality readily-usable data and the recognition that local environments matter for both short and long-term outcomes (Algan et al. 2016, Chetty and Hendren 2018, Gould et al. 2004; 2011, Kuhn et al. 2011, Ludwig et al. 2013). This paper follows that trend by introducing the LNG, a novel measure of local inequality with several appealing properties. First, geolocated real estate data makes the LNG independent of administrative boundaries — a longstanding obstacle present even when data availability is at granular levels of aggregation (e.g., census tracts), and that significantly complicates performing

correlated with actual income rank at the neighborhood level. Minkoff and Lyons (2019) showed that individuals living in more "income diverse" (but not income unequal) neighborhoods in New York perceived a higher income gap between "the rich and everyone else".

[2]The former paper "shocks" local environments by randomizing the presence of a luxury car in South Africa in a field experiment. The latter randomizes exposure to a poor-looking person in Boston. Both papers measure demand for redistribution using respondents' support for a tax on millionaires.

analysis over time (Openshaw and Taylor 1979, Wong 2009). Second, the LNG is easily harmonized and replicable across contexts. Similar geolocated real estate data is available in many countries, and the nature of the data guarantees a high degree of homogeneity across contexts.[3] Finally, the LNG measures a non-standard but relevant form of inequality, housing inequality. Housing is the most important asset for most households across the wealth distribution (Martínez-Toledano 2017), and studying differences in its consumption is informative about disparities in living standards.

2 The Local Neighborhood Gini: a novel measure of local inequality

2.1 The Local Neighborhood Gini (LNG)

The LNG captures a dimension of housing inequality in the immediate local environment of a dwelling. I motivate the measure with a toy example in Web Appendix A. To construct the LNG, one must first decide the inequality dimension to study. The choice set will depend on data availability. Given that geolocated real estate data will be a key component, housing space or value are natural candidates. The second step is to determine the spatial scope of the neighborhood or, in other words, decide how "local" a local neighborhood ought to be. This is captured by the parameter r. The LNG defines a local neighborhood as the set of properties contained within an r-meter buffer around a given dwelling.[4] The application at hand should guide the choice of r. Finally, the LNG is simply the Gini index of that local neighborhood.

2.2 Construction in practice: data

Cadastre data: The primary data source to construct the LNG for Barcelona (and other Spanish cities) is the Spanish Cadastre (*Catastro*), a registry of the universe of the real estate present in the country provided by the Spanish Ministry of the Treasury for taxation purposes.[5] The Cadastre data is exceptionally detailed and accurate. For every real estate unit in the country (e.g., an apartment), one can observe the exact location, size (in square meters), year of construction, years in which the unit was subject to renovations (if any), quality,[6] and the primary use (e.g., residential, retail, or cultural). The data comes with the GIS cartography, thus facilitating precise geolocation. The dataset is updated twice per year, and it offers a snapshot of the Spanish real estate at the time of the update. The data is publicly available.[7] The complete dataset also contains ownership and a value assessment of all properties (*valor catastral*), but these latter features are confidential.

[3]The key elements to construct the LNG are the location of the real estate and some of their characteristics (e.g., size). These leave little room for arbitrary definitions.

[4]While the idea of defining a local neighborhood by "drawing a circle" around some point is not new (Lee et al. 2008, Reardon and O'Sullivan 2004), in practice, all attempts to implement such an approach ultimately relied on aggregated data (e.g., at the census tract level). The LNG is based on geolocated housing data and, therefore, can circumvent this problem.

[5]The data does not include the real estate located in the Basque Country and the Navarra regions, as these have a special taxation regime.

[6]Quality is measured on a scale from 1 to 9.

[7]See https://www.sedecatastro.gob.es/.

With the Cadastre data alone, I could compute the LNG capturing dispersion in dwelling space. I employed real estate transactions data from the Catalan Tax Agency (*Agència Tributària de Catalunya*, ATC) to measure dispersion in dwelling value.

ATC administrative data: This dataset contains information on the universe of real estate transactions in Catalonia from January 2009 to December 2019. The data source is the property transfer tax (*Impuesto de Transmisiones Patrimoniales*, ITP), a tax levied on real estate transactions involving existing homeowners and new buyers. This tax only applies to transfers of used property.[8] During this period, there were over 275,000 transactions, 65,000 of which took place in Barcelona. For each transaction, the data contains the property's value, some of its characteristics (e.g., size or year of construction), its geographic coordinates, and, critically, the Cadastre identification code. This latter feature facilitates merging the ATC data with the Cadastre.[9]

Other data sources: I complemented the ATC and Cadastre data with demographic information from the Municipal Registry (2009-19); the 2011 Census; income data from INE's *Atlas de distribución de renta de los hogares* (2017); rental price data from the Ministry of Transportation (2017) and the Barcelona City Council (2009-19); and public transportation data from Barcelona Transportation Authority (2019).

I combined all the previous sources to estimate the value of all dwellings in Barcelona using a Random Forest algorithm (Breiman 2001). The web appendix contains the estimation details.

2.3 Construction in practice: algorithm

I construct the LNG in five steps. First, I select a building plot in a city.[10] Second, I choose r and draw an r-meter buffer with origin at the plot's centroid. The present research question calls for a small r. Any specific choice of r is arbitrary, so I produced the LNG applying multiple buffers — from 100 meters to one kilometer — and decided to let the data suggest to me what "the relevant" r is (see next section). In the third step, I select all the plots whose centroids intersect with the r-meter buffer. I say that all the *dwellings* in these plots constitute the building's "local neighborhood." Figure 1 illustrates this step. In the fourth step, I compute the Gini index for the local neighborhood, thus summarizing the dispersion in dwelling values (or sizes) in the area. That number is the LNG specific to the building.[11] Finally, I repeat steps one through four for every plot in the city. Figure 2 shows the results for Barcelona ($r = 100$).

The web Appendix compares LNG estimates for Barcelona and other Spanish cities with tradi-

[8] A different tax — the *Impuesto sobre Actos Jurídicos Documentados* (IAJD) — is levied on the acquisition of new property.

[9] The Cadastre code in the ATC data links a transaction to a building in Catalonia, but not to the exact unit within that building. To effectively link both datasets, I looked for the best match using other information available in the ATC — year of construction/renovation, unit quality, and size.

[10] A plot is the land over which a building is constructed.

[11] The LNG varies at the building/plot level, but all dwellings within the building and surrounding buildings (of the local neighborhood) are used when computing the Gini index.

tional income inequality measures. I find that income inequality is generally larger than housing value or space inequality.

3 The survey

3.1 Sample

Netquest, a market-research company based in Barcelona, carried out sample recruitment. Fieldwork started on May 28 and was completed on June 9, 2020. Each respondent completing an estimated 15-minute long survey received approximately three USD (in "koru points" — a virtual currency).[12] I instructed Netquest to sample respondents from all (10) districts and (73) neighborhoods in Barcelona while maintaining a balanced sample in terms of gender, age, and socio-economic status to the extent possible. In total, 1,444 respondents completed the survey. I discarded 114 of them for different reasons.[13] The final sample includes 1,330 individuals.[14]

Table 1 compares the Netquest sample with the target population in Barcelona. The sample is reasonably well-balanced in terms of age, marital status, rental status, employment status, and household characteristics. It is imbalanced in terms of gender (males overrepresented), origin (foreign-born underrepresented), education (university graduates overrepresented),[15] and ideology (left-wing individuals are overrepresented).[16] Table B1 shows the geographical distribution of the sample across districts and neighborhoods. All districts and neighborhoods are represented and the geographic balance is good. Still, some districts are slightly underrepresented (Ciutat Vella, Les Corts), while others are overrepresented (Sants-Montjuïc, Sant Martí).

3.2 Design: eliciting perceived inequality and preferences for redistribution

Preferences for redistribution: I measure preferences for redistribution using the Spanish translation of the following question:

"Some people think that public services and social benefits should be improved, even at the expense of paying higher taxes (on a scale from 0 to 10, these people would be at 0). Others think that it is better to pay fewer taxes, even if this means having fewer public services and social benefits (these people would be at 10 on the scale). Other people are in between. In which position would you place yourself?"

I chose this question because it is the official adaptation to the Spanish language of a question in the General Social Survey (GSS) commonly used to study distributional preferences (e.g., Alesina

[12]The final median completion time was 18 minutes. Netquest compensated all respondents participating in the survey, even when they did not complete it. They do so to maintain the high quality of their online panel.

[13]99 could not be matched to a valid address. The most common reasons were: the participant introduced a ZIP code from outside Barcelona, typos in the address, and the inexistence of the address. 15 due to inconsistencies between their responses and Netquest's records (e.g., mismatch in gender or age).

[14]The web appendix contains a detailed description of the survey and the complete list of questions translated into English.

[15]Note that the latter comparison comes from the 2011 census. The imbalance at the time of the survey was possibly less exaggerated.

[16]Note that part of the imbalances are common features of online samples, typically composed of younger and more educated individuals.

and Giuliano 2011).[17] The adaptation was carried out by the sociologists working at the Spanish *Centro de Investigaciones Sociológicas* (CIS) and has been used in many of their surveys, including the *Encuesta Social General Española*, a survey entirely adapting the GSS in the Spanish context. Therefore, this question allows for a suitable framing of results in the context of the existing literature.[18]

Perceived inequality: I measure perceived inequality by eliciting respondents' perceived national income distribution first. I then compute the implied Gini coefficient of the distribution. Figure B1 shows the question I used. Specifically, after explicitly defining income and indirectly introducing the notion of income distribution in two previous questions,[19] I asked respondents about their perceived incomes at the percentiles 10, 30, 50, 70, 90, and 99. From those, I could back up the entire distribution by applying linear interpolation.[20] Obtaining the corresponding Gini index (or any other standard measure of inequality) is then straightforward. A similar approach is followed in Eriksson and Simpson (2012) and Chambers et al. (2014), where they measure perceived inequality by computing the ratio of perceived income/wealth between the percentiles 80 and 20,[21] or in the recent work by Hvidberg et al. (2020), where they measure perceived income in the percentiles 90 and 50.

I chose to elicit the income (and not wealth) distribution for several reasons. First, defining income as a concept is more straightforward, as it does not require using words such as "asset" or "debt." Second, relative to wealth, individuals are more likely to have a better idea of others' incomes and salaries. Third, the timing of the survey coincided with the Spanish tax season (April-July). That meant that personal and household income should have been salient at the time of the survey as almost everyone has to file for the income tax. Very few individuals file for the wealth tax.[22] Finally, most of the literature studying the relationship between inequality and distributional preferences has focused on income rather than wealth (Gimpelson and Treisman 2018, Karadja et al. 2017, Niehues 2014).

The median respondent did reasonably well in guessing the shape of the actual income distribution. Figure 3 shows the distribution of *perceived income* across the different percentiles surveyed. For example, the median perceived income in the 10th percentile is 500 euros, whereas the actual income in that percentile is 446 euros (ECV, 2018). Nonetheless, individuals significantly overestimate income at the top — particularly in the percentiles 90 and 99.[23]

[17] The exact question in the GSS reads: *"Some people think that the government in Washington should do everything to improve the standard of living of all poor Americans (they are at point 1 on this card). Other people think it is not the government's responsibility, and that each person should take care of himself (they are at point 5). Where are you placing yourself on this scale?"*.

[18] I rescaled values from the question so that a 10 represents the highest demand for redistribution.

[19] All questions avoid complex words such as "percentile" or "distribution." Instead, I introduce these notions by talking about (and showing) a scale that orders households in the country by income.

[20] I assigned an income of 0 to the first percentile.

[21] Eriksson and Simpson (2012) asked the question: *"What is the average household wealth, in dollars, among the 20% richest households in the United States?"* Chambers et al. (2014) asked the same question, but eliciting income instead of wealth.

[22] The reason being a high minimum exemption threshold, currently set at 700,000 euros of net wealth. Few individuals or households surpass that threshold. For context, in Catalonia in 2018, there were 3,655,487 income tax filers (Agencia Tributaria 2018a), but only 77,397 wealth tax filers (Agencia Tributaria 2018b).

[23] Chambers et al. (2014) document a similar result.

Individuals overestimate national-level inequality. Figure 4 shows the distribution of perceived inequality in the sample. The mean *Perceived Gini* is 0.45, and the median is 0.42, both values are above the actual Gini of 0.36 (ECV, 2018). That is a consequence of the overestimation of top incomes.

4 Descriptive results

4.1 The determinants of perceived inequality and preferences for redistribution

I start by studying the determinants of perceived inequality and demand for redistribution in Table 2. In this table, and all tables throughout the paper, I standardize all continuous variables to facilitate the comparability of results.

Columns 1 and 2 show that males, college graduates, higher-income households, and left-wing individuals perceive significantly more inequality. District fixed effects do not explain these patterns. For example, relative to a right-wing individual, left-wingers perceive approximately 25% of a standard deviation (SD) more inequality (4.5 points, 10% of the variable mean).[24] This result is consistent with Chambers et al. (2014), which finds that US liberals perceive significantly more inequality.[25] To the best of my knowledge, no existing studies show how inequality perceptions correlate with other individual characteristics.

Ideology is the most important determinant of demand for redistribution. Perceived inequality is also relevant. I explore the correlations between preferences for redistribution and individual characteristics in Columns 3-5. Column 5 suggests that, relative to right-wing individuals, left-wingers demand approximately 75% of a SD more redistribution (1.75 points, 27% of the mean). This result is consistent with what Alesina and Giuliano (2011) (AG11) and others typically find. Perceived inequality is another major determinant, albeit its relative importance is significantly (about five times) smaller. These findings are consistent with previous research (Gimpelson and Treisman 2018, Niehues 2014). The direction of the correlation for the other determinants generally goes in the same direction as well. Comparing them with AG11, the sign coincides when looking at gender (females generally more willing to redistribute), religion (religious individuals less willing to redistribute, according to the World Value Survey), employment status (unemployed more willing to redistribute). In AG11, the sign for age and marital status flips across specifications, but it is typically not statistically different from zero. The sign does not coincide when looking at college graduates and higher-income individuals (both usually less willing to redistribute in AG11).[26] Table B2 studies the relationship between *Preferences for Redistribution* and other major drivers according

[24] *Left-wing* is an indicator taking a value of 1 if the individual responded with value between 0 and 4 to the following question: *"When talking about politics, it is common to use the expressions "left" and "right." On a scale from 0 to 10, where 0 means "very left-wing" and 10 "very right-wing," where would you place yourself?"*

[25] According to their measure (the 80/20 income ratio), liberals perceive up to 30% more inequality than conservatives (Figure S3 in their Appendix).

[26] Although not shown in the table, the pattern can be explained by heterogeneity along the ideology dimension. Higher-income and highly educated left-wing individuals are more favorable towards redistribution. The opposite (non-significant) is true for right-wing individuals.

to the literature. All correlations have the expected sign, and inequality perceptions are among the most prominent determinants.

Overall, the correlations presented in the table are consistent with our knowledge about beliefs about inequality and demand for redistribution.

4.2 LNG, perceived inequality, and preferences for redistribution

Perceived inequality: I start investigating the association between local and perceived inequality by estimating the following model:

$$Y_i = \beta LNG(r)_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{1}$$

where Y_i is individual's i perceived inequality (*Perceived Gini*), $LNG(r)$ is the LNG with an r-meter buffer associated with the dwelling of the respondent. X_i is a battery of individual and neighborhood controls. Individual controls include age, log household income, household size, and indicators for female, foreign-born, college education, married, religious, left-wing ideology, home-renter, and unemployed. Neighborhood controls (measured at the census tract level) include population density,[27] median apartment size (log square meters), median apartment quality, median year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. $\delta_{i(j)}$ is an indicator taking the value of 1 if individual i resides in district j. Standard errors are clustered at the neighborhood level.[28]

The top panel in Table 3 shows the OLS estimates of Equation 1 with the definition of local neighborhoods (characterized by r) broadening across columns, ranging from 100 meters to one kilometer. The first six columns show the estimates without the vector of controls. The last six include controls. Figure 5 (left panel) plots the same regression coefficients to visualize better the patterns that emerge in the table.

Local inequality is positively correlated with perceived inequality in narrowly-defined neighborhoods ($r \leq 500$). For example, when $r = 200$ (Column 8), a 1 SD increase in LNG yields a significant shift in *Perceived Gini* of approximately 10% of a SD (translating into 1.8 points in that variable, or 4% of the mean). The sign quickly decays and eventually flips as the neighborhood's definition gets wider (as r increases).

The inclusion of controls does not make a big difference. Keeping r fixed, the point estimate obtained with or without controls is virtually identical. These results suggest that, even in the presence of residential sorting, the effects of local inequality on perceived inequality are relatively homogeneous, at least conditional on observables. They do not imply that unobservables are irrelevant, but they point in that direction (Oster 2019).

[27]The census tract is the smallest level of aggregation at which some statistics are reported. They typically contain less than 1,500 individuals.

[28]Barcelona has 10 districts (*districtes*) divided in 73 neighborhoods (*barris*).

Preferences for redistribution: The bottom panel in Table 3 studies the relationship between local inequality (LNG) and distributional preferences by re-estimating Equation 1 with *Preferences for Redistribution* as the dependent variable. Figure 5 (right panel) plots the regression coefficients.

If anything, there is a negative relationship between local inequality and demand for redistribution. The association is null (or mildly positive) in extremely narrow neighborhoods ($r < 200$). It becomes more negative (but always indistinguishable from 0 in the specifications with controls) the larger r is.

The results are consistent with local inequality affecting demand for redistribution through perceptions. Results in Table 2 (Column 5) indicated that demand for redistribution increases by approximately 14% of a SD (0.33 points) following a 1 SD shift in *Perceived Gini*. Top Column 8 in Table 3 suggests that perceived inequality would increase by approximately 10% of a SD (1.8 points) following a 1 SD increase in LNG. This shift in perceived inequality would only translate into an increase in demand for redistribution of 0.033 points (1.4% of a SD, or 0.5% of the mean). The implied coefficient (0.014) is actually contained within a 95% confidence interval of the point estimate in Bottom Column 8 of Table 3.[29] Therefore, the relatively weak association between local and perceived inequality, and between perceived inequality and demand for redistribution, can explain the essentially null relationship between local inequality and demand for redistribution from the bottom panel in Table 3. Other studies have found similar results.[30]

The inclusion of controls matters, especially in broadly defined neighborhoods. When r is small, the difference in a given column comparison (with versus without controls) is not statistically significant. However, when $r > 500$, the difference between the two becomes apparent. Specifically, when no controls are included, the relationship between local inequality and redistribution preferences is negative and highly significant. That suggests that sorting on some observable characteristic might take place. I explore this hypothesis in Table B3, where I regress the LNG associated with individuals' dwellings on their observable characteristics while varying r across specifications.

Sorting along ideology can explain the previous pattern. Table B3 makes clear that ideology is the primary individual characteristic that varies as the neighborhood's spatial scope broadens. When the neighborhood is narrowly defined, there are no significant differences across individuals in practically any dimension.[31] However, as the definition of local neighborhoods broadens, it soon becomes clear that left-wing individuals are less likely to be represented in the more unequal parts. To get a sense of the magnitude, Column 5 ($r = 750$) implies that, in a local neighborhood that is a 1 SD more unequal than average (+4.7 points in LNG), left-wing individuals are approximately

[29] This is also true for the rest of the estimates in the last six columns. These would be: 0.008, 0.014, 0.007, 0.001, -0.006, -0.011.

[30] Sands and de Kadt (2019), in the context of South Africa, construct a measure of income inequality by aggregating census tracts. They find that a 1 SD increase in their local inequality measure is associated with a 0.8pp increase in their measure of preferences for redistribution (support for a tax on the wealthy). A small effect. Also similar to this paper, they find that measuring local inequality aggregating census tracts beyond one kilometer yields a negative association with demand for redistribution.

[31] At $r = 100$, older and single individuals are somewhat more likely to reside in locally unequal neighborhoods (10% significance level).

13.5% *less* likely to be represented. This finding is consistent with left-wing individuals (liberals) disliking inequality more than conservatives (Napier and Jost 2008), and suggests the presence of significant sorting along this characteristic. Left-wing individuals are generally more in favor of redistribution (Table 2). Therefore, not controlling for this individual characteristic biases the estimates in Table 3 downwards.[32]

The previous associations could be interpreted as a lower bound, at least in terms of precision, if the LNG captured disparities in local income (rather than wealth). A caveat to the previous results is their interpretation. The outcomes studied measure perceived *income* inequality and preferences for *income* redistribution, but the LNG measures local *housing value* inequality — a dimension of wealth inequality. Housing consumption is positively related to income (i.e., richer individuals tend to live in more valuable houses),[33] but that relation is not one-to-one. Thus, one could interpret the LNG as a measure of income inequality with some noise. Under this interpretation, we should expect the results presented in Table 3 to be more precisely estimated if a measure of local income inequality was available.

Overall, results show that local inequality is associated with perceived inequality but not with demand for redistribution. The latter association is, if anything, negative, especially in local neighborhoods characterized by a large r. A perhaps counterintuitive result, explained by sorting on ideology. The presence of sorting calls for caution when interpreting the previous correlations, as sorting on unobservables could also be there. To get at causality, it is necessary to find a setting with plausibly exogenous variation in local inequality. I will exploit the rise of new apartment buildings as a shock to local neighborhoods.

5 The rise of new apartment buildings as a quasi-experiment

5.1 Identification and empirical strategy

I exploit within-neighborhood variation caused by the rise of new apartment buildings as a plausibly exogenous shock to local environments. Figure 6 illustrates the intuition behind this approach. The top panel there shows an apartment building in Barcelona. As suggested by the image and confirmed by the Cadastre data, all apartment units in the area are similar. This is reflected in a low LNG (0.02, $r = 100$) associated with that building in that year (2012). The bottom panel shows the same apartment and its surroundings three years later, in 2015. Noticeably, a new and modern apartment building was constructed over a former parking lot. The new units are considerably larger and of better quality and, therefore, the LNG ($r = 100$) of the old building jumped to 0.23 — a tenfold increase relative to 2012. The two buildings are in stark contrast to each other, which might have disrupted the way dwellers “close” to the new building see their neighborhood.[34] This

[32]Even if not shown in the table, that is effectively the case. Controlling for the full battery of observables omitting ideology yields a negative (and often significant) relationship between LNG and demand for redistribution.

[33]Certainly under the theory of permanent income.

[34]Most of the new apartments are of a superior quality. According to the Cadastre data and my value predictions, relative to the dwellings of treated respondents, new apartments are of equal or higher quality in 90% of the cases. They

approach exploits shocks of this nature by taking advantage of the fact that survey respondents' exact addresses are observed.

Following the intuition illustrated in the previous example, I estimate the model below:

$$Y_i = \beta Treated_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{2}$$

where Y_i is an outcome variable of interest (e.g., perceived inequality) of individual i. $Treated_i$ is an indicator variable taking the value of 1 if the individual resides within 350 meters of a new apartment building constructed in the previous three years before the survey (2017, 2018, or 2019). X_i and $\delta_{i(j)}$ are defined as in Equation 1, except for the fact that "neighborhood controls" are now measured in 2015 (before the treatment) and include the 2015 value LNG ($r = 350$) associated to respondents' dwellings.

Figure 7 shows the distribution of new apartment buildings in Barcelona and offers an additional visualization of the identification strategy. The map shows Barcelona divided by its ten districts. Red symbols represent the exact locations of new apartment buildings constructed in 2017-19. Orange circumferences surrounding the symbol represent 350-meter buffers around the buildings. All individuals in the sample residing within one of those buffers are defined as treated. The rest serve as controls.

In words, the identification assumption is that, conditional on the battery of controls, new buildings' locations are not systematically related to unobservable characteristics of individuals within a district. If true, then β causally identifies the effect of new constructions on the outcomes of interest — perceptions and redistribution preferences.

Identification is plausible. The treatment exploits the rise of new *apartment* buildings, not museums, churches, or other iconic buildings. Tens of new developments are constructed every year throughout the city and, unlike in the US, Barcelona residents do not influence the licensing approval process.[35] Moreover, to address the potential threat of individuals strategically locating in neighborhoods that are "improving" faster over time relative to others (gentrification), the baseline specification restricts the attention to individuals that have lived in the same dwelling for at least five years. In robustness, I further extend the residency requirements (to up to fifteen years) and restrict my attention to property owners — arguably less mobile than renters.

The 350-meter buffer choice responds to the local nature of the treatment. Section 4.2 suggested that the "relevant" spatial scope of a local neighborhood might be somewhere between 200 and 500 meters. 350 is the middle point. Also, intuitively, individuals residing closer to the new building are more likely to notice it. That is less true for individuals living farther.

The small clusters of new constructions over short time horizons and legislation justify the three-year treatment time window. As Figure 7 makes clear, a local neighborhood treated in 2019 is also likely to have been treated in 2018 or 2017. These clusters could, in part, illustrate different

are more spacious and more valuable in approximately 80% of the cases.

[35]The city council is the entity in charge of granting licenses to developers. The process is clearly regulated, and the city council does not have much discretion. A developer will generally obtain the license unless the building characteristics conflict with existing urban regulations (e.g., on building height) (*Pla d'Ordenació Urbana de Barcelona*).

buildings from the same development project completed in different calendar years. Also, defining an individual exposed to a new building in 2018 but not in 2019 as untreated could be problematic if treatment effects persist for over one year. Finally, the law gives developers three years to complete their projects after obtaining their license.[36] In robustness, I explore the sensitivity of the results to different time windows.

New building treatment and local inequality: Table 4 investigates the effects of the treatment on the change in local inequality. Given that dwelling prices are estimated from real estate transactions on *used* (i.e., not new) properties,[37] predictions are likely to substantially underestimate the value of new houses or apartments — and hence the change in local inequality induced by the new apartment building.[38] Therefore, in addition to looking at the average effects on local inequality in dwelling value in Columns 1-3, I also look at changes in dwelling space inequality in Columns 4-6. Across rows, I vary r and the distance to enter the treatment sample jointly, from 200 to 500 meters.

Local inequality increases following the rise of a new apartment building. That is true for value and space, although the increase is only significant when looking at space. In terms of the magnitude, baseline results (Columns 2 and 4) suggest that a new apartment building increases local value and space inequality in respondents' neighborhoods by approximately 8% and 32% of a SD, respectively. These translate into $+0.73$pp for value and $+0.26$pp for space, or 6 and 130% of the mean, respectively.[39] Magnitudes are similar when considering events within 200 or 500 meters instead (Columns 1, 3, 4, and 6).

Covariate balance: The covariate balance between treatment and control samples is good. Panel A in Table B4 shows that none of the groups significantly differs in observed individual characteristics. There are some differences in local neighborhoods. Panel B shows that treated areas are slightly more populated — they have higher population density ($+0.004$ persons per square meter) and smaller apartments (-4 square meters) — and have fewer immigrants (-3pp). They do not differ in local inequality, left-wing vote share in the 2015 elections, apartment quality, or building construction year.

5.2 New building treatment, perceived inequality, and preferences for redistribution

Perceived inequality: The top panel in Table 5 investigates the effects of the new apartment building treatment on perceived inequality. Across the table, odd columns show the β estimates of Equation 2 without the battery of controls. Even columns include controls.

[36] Article 189.1 of the *Text Refós de la Llei d'Urbanisme* states that developers have, by default, one year to start the construction and up to three years to complete it following the license approval.

[37] See Section A.2 for details.

[38] Even when *Year of Construction* is one of the variables included in the estimation algorithm. New dwellings transactions should be incorporated in the estimation sample to predict their value accurately.

[39] As argued earlier, the effects on local value inequality are likely to represent a lower bound.

Exposure to a new apartment building increases perceived inequality. Column 2 (the baseline specification) shows an average treatment effect of approximately 18% of a SD, translating into an increase in *Perceived Gini* of about 3 points (7% of the mean). Columns 3-6 further restrict the sample to individuals that have resided in the same dwelling for at least 10 or 15 years to alleviate concerns on hypothetical anticipatory effects. The rationale is that moving into a (local) neighborhood anticipating the rise of a new apartment building ten years into the future is more implausible. By applying these restrictions, the magnitude fluctuates between 16 and 21% of a SD, translating into an increase of 3-3.5 points in *Perceived Gini*. Results are inconsistent with anticipatory effects. To address the concern of displacement effects (individuals moving *after* the rise of a new building), Columns 7-10 explore heterogeneity by rental status. The rationale is that, relative to renters, moving costs are substantially higher among homeowners (e.g., they might have a mortgage).[40] We should therefore be less worried about this concern in the homeowners' sample. Point estimates are slightly larger and more precise in the homeowners subsample (17.5% of a SD, Column 10), but they are not significantly statistically different from the estimates in the renters' subsample (15.7% of a SD, Column 8). These results are inconsistent with significant displacement effects.

Preferences for redistribution: The bottom panel in Table 5 investigates the effects on preferences for redistribution.

The treatment has a mild (positive) effect on demand for redistribution. Baseline results from Column 2 show that recent exposure to a new apartment building increases demand for redistribution by approximately 3.5% of a SD (0.08 points, or 1.3% of the mean). However, the coefficient is not statistically significant. The following columns investigate this result's sensitivity by restricting the sample to individuals having resided in the same dwelling for longer or to either renters or homeowners alone. Point estimates across columns consistently show small positive effects, reaching a 10% significance level at most in the specifications without controls.

Overall, Table 5 suggests that individuals exposed to a new apartment building perceived about 7% more inequality, but only increased their demand for redistribution by about 1%, with zero effects impossible to rule out.

5.3 Robustness

In this section, I explore the sensitivity of results to alternative identification strategies, distance thresholds (200 and 500 meters), time windows (one and two years), and outcomes (alternative measures of perceived inequality and demand for redistribution). I also present results from an IV approach. Figures 8 and 9 offer a snapshot of the section by summarizing results in specification curves.

Alternative distance thresholds and identification strategies: Figure B2 illustrates the alternative

[40] 42% of homeowners in the sample have pending payments on their dwelling.

identification strategies that I explore. Panel (a) offers a visualization of the baseline identification. In the figure, a triangle represents a new construction, and the small circumferences of different colors represent the location of individuals in the sample scattered across the district. The large (red) circumference surrounding the triangle illustrates the district's treated area (350m in the baseline), whereas the rest of the polygon (colored in light-blue) represents the control area. The small circumferences' colors highlight the individuals' treatment status — red for treated and blue for control. A concern on the baseline identification is that individuals who are too far away from the new construction might differ in unobservables relative to those closer. A solution is to follow the "ring identification" illustrated in panel (b). Building from the baseline, this approach involves choosing a second threshold (the outer ring) and leaving all individuals in its interior out of the sample. These correspond to the small circumferences colored in black. Similar approaches have been previously used in other contexts (Autor et al. 2014, Deshpande and Li 2019, Shoag and Veuger 2018). A caveat is that if both the inner and outer ring distances are too severely restricted, a zero effect could arise in the presence of spillovers to control observations. A "double ring identification" strategy could address this concern. The idea is simple: if using individuals in the outer ring's interior is problematic due to spillovers, then use individuals in the exterior of the outer ring as controls — they are going to be less subject to these spillovers. Panel (c) illustrates this latter strategy. Each approach has strengths and weaknesses. I explore the three of them while varying the threshold distances (inner and outer ring) from 200 meters to one kilometer.

Tables B5 (*Perceived Gini*) and B6 (*Preferences for redistribution*) explore robustness along these margins. In both tables, baseline estimates correspond to Column 4 in Panel A. A quick look at the tables delivers the following conclusions. First, the treatment increased perceived inequality. The most conservative estimate is an increase of 4% of a SD deviation (that would translate +0.7 points in *Perceived Gini*; Column 2 in Panel B). The least conservative estimate is approximately 40% of a SD (that would translate in +7 points in *Perceived Gini*; Column 6 in Panel C). Second, the effect on preferences for redistribution is likely to be positive, but close to zero. Estimates range from -0.01% of a SD (Column 6 in Panel B) to 19% of a SD (Column 3 in Panel C), which would translate into an increase ranging from 0 to 0.4 points in *Preferences for Redistribution*. Zero effects cannot be ruled out, but estimates are consistently positive (except in one specification). Third, the comparison of Panels B and C suggests the presence of spillover effects. Comparing estimates from Columns 1 and 2 in Panel B with those from the rest of the table makes that point salient. Note that, in these two columns, the inner ring is 200 meters, and the outer ring is 500 meters — therefore, the no-spillover assumption would imply that treatment effects do not span beyond 200 meters. The estimates in the rest of the columns challenge that assumption.

Alternative distance thresholds and time windows: The baseline specification considers an individual treated if exposed to a new building within the previous three years before the survey. Here I explore the sensitivity of the results to tighter time windows (of one and two years) while also varying the distance threshold, as in the previous exercise (200, 350, and 500 meters). Tables

B7 (perceived inequality) and B8 (preferences for redistribution) show the results of this exercise. Panel A replicates the baseline results, where an individual is treated if exposed to a new building in the past three years. Panels B and C restrict the time window to two and one years, respectively. In both tables, odd columns make use of the baseline sample — where the only restriction applied is having resided in the same dwelling for at least five years. Even columns further restrict the sample to individuals not exposed to a new building *before* the time window considered (from 2017). In practice, this means that, in Panel C, individuals exposed to a new building in either 2017 or 2018 are excluded. In Panel B, individuals exposed to a new building in 2017 are excluded. No further restriction is applied in Panel A.[41] The rationale for these further restrictions is to test the persistence of treatment effects. If effects are persistent, then estimates in specifications that include individuals previously treated (odd columns) should systematically be smaller.

Results in both tables suggest an increase in perceived inequality and a (much smaller) increase in demand for redistribution following exposure to a new building. They also suggest that treatment effects are not short-lived. The latter point is more evident when comparing odd and even columns in Panel C, as the even column always shows a larger point estimate. Also, even columns' coefficients are generally more precise (with higher t-statistics) despite being estimated with smaller sample sizes. The same conclusions apply when looking at Panel B (two-year window) — although the differences between odd and even columns are not that stark. Overall, this exercise suggests an increase in *Perceived Gini* ranging between 0 and 28% of a SD (up to +4.8 points, 11% of the mean), and an increase in *Preferences for Redistribution* ranging between 0 and 11% of a SD (up to +0.25 points, 4% of the mean).

IV: Tables B9 and B10 present results following an IV approach, where I instrument recent variation in LNG using the new apartment building shock. As Table 4 hinted, results using Δ*LNG (Value)* are noisy due to a weak first stage. I will therefore focus the discussion on Δ*LNG (Space)* (Columns 5-8 in both tables).

IV estimates provide further evidence of the link between local inequality, perceptions, and demand for redistribution. OLS estimates (Columns 5-6 in both tables) are substantially smaller than the IV (Columns 7-8), suggesting the presence of downward bias in the OLS. In terms of magnitude (Columns 7-8), one SD increase in Δ*LNG* translates into an almost 50% of a SD increase in *Perceived Gini* (9 points, 20% of the mean), and with approximately 8% of a SD increase (not significant) in *Preferences for Redistribution* (0.19 points, 3% of the mean). These magnitudes are substantially larger than those in the reduced form specifications (Table 5). Thus, at face value, Tables B9 and B10 provide even stronger support of the connection between local environments, perceptions, and demand for redistribution. Nevertheless, results are only valid under the assumption that the new apartment building treatment only affects the outcomes of interests through changes in local inequality. Some may consider that exclusion restriction too stringent given the context. Results ought to be interpreted with that caveat in mind.

[41]Therefore, even and odd columns report identical estimation results in that panel.

Specification curve: By varying the definition of treatment and control, the sample restrictions, and the covariates included, or the estimation method, a total of 325 different specifications are possible up to this point. I summarize all of them in Figures 8 and 9. Both figures report the estimated effect of the treatment on *Perceived Gini* or *Preferences for Redistribution* in a given specification. The bottom panel describes the characteristics of the specification.[42]

The positive effect of the treatment on perceived inequality and demand for redistribution is evident. Figure 8 shows that the estimated effect on *Perceived Gini* is positive in 317 of the 325 specifications (97.5%). It is significant at the 90 and 95% level in 168 and 111 specifications, respectively. When the coefficient is negative (eight occasions), it is never statistically different from zero. The lowest value is -0.04, and the largest is 1.53. The mean value is 0.34 — doubling the size of the baseline estimate (marker in blue). Figure 9 looks at *Preferences for Redistribution*. Coefficients are positive in 303 specifications (93.2%). They are significant at the 90 and 95% level in 49 and 22 specifications, respectively. When negative, they are not statistically different from zero. The lowest value is -0.09 and the largest 1.35. The mean value is 0.16 — almost five times the size of the baseline estimate. In both figures, the lowest values correspond to specifications estimating treatment effects using the ring identification in narrow distances, indicating the presence of spillovers. Overall, results overwhelmingly point at a positive effect on perceived inequality. The effects on demand for redistribution go in the same direction, but they are significantly smaller (very close to zero) in magnitude.

Alternatives to *Perceived Gini*: I use three alternative variables capturing perceived inequality. The first two are the perceived log 90/10 and 90/50 income ratios, generated from the same question as *Perceived Gini*. The third alternative comes from a question borrowed from the International Social Survey Programme (ISSP). In that question, respondents are confronted with five pictures of pyramids representing hypothetical societies and are asked to choose the one that best represents Spain in their view. Figure B3 shows the question. The question is rather abstract, but some papers have used it to measure inequality perceptions (e.g., Gimpelson and Treisman 2018, Niehues 2014). Here I follow Gimpelson and Treisman (2018) and assign a "Perceived Gini" to each respondent based on the inequality that can be inferred from the pyramids.[43] Table B11 shows the results, where I also vary the distance thresholds (i.e., 200 meters in Columns 1-2, 350 meters in Columns 3-4, and 500 meters in Columns 5-6).

Results using the income ratios (in the top two panels) confirm that the treatment increases perceived inequality. The point estimates are generally larger and more precise relative to the baseline. They range between 17 and 23% of a SD increase in the outcome of interest. The ISSP

[42]These are: the estimation method (reduced form or IV), the covariates (inclusion of controls or not), the definition of treatment group (variation with distance and time), the definition of the control group, and the sample restrictions (minimum residence requirement).

[43]The paper measures each bar's relative size (within a pyramid) and then computes an implied Gini index. The resulting coefficients for each of the diagrams are: (A) 0.42, (B) 0.35, (C) 0.30, (D) 0.20, (E) 0.21.

question results are in the same direction, but coefficients are smaller and statistically insignificant.[44] That question is probably capturing a different form of perceived inequality (other than income), which could explain the small discrepancy in the results.[45]

Alternatives to *Preferences for Redistribution*: I use a different survey question and electoral outcomes as alternative measures of demand for redistribution. The survey question is borrowed from Fehr et al. (2019), and reads as follows:

How much income redistribution (through taxes and transfers from the state) would you like to see in Spain? No redistribution, 0 in the scale, means that the state does not redistribute any income. Maximum redistribution, 10 in the scale, means that, after the redistribution, everyone has exactly the same level of income.

The baseline demand for redistribution measure gave participants an explicit trade-off between better public services and social benefits and taxes. This question is less explicit about the trade-off involved in the redistribution process.

Regarding electoral outcomes, I consider two variables. First, an indicator taking the value of one if the respondent voted for a left-wing party in the November 2019 national election.[46] Second, the vote share obtained by the same left-wing parties in the same election measured at the census tract level. I construct the latter variable from aggregate electoral data obtained from the Ministry of the Interior.

A vote for a left-wing party is not necessarily equivalent to the desire to redistribute more, but it can be a good proxy. Parties offer a menu of policies in their electoral platforms, some about redistribution, and others not. Nevertheless, redistribution is typically a salient topic in electoral campaigns, with left-wing parties advocating for higher taxes and better public services. Besides, studying electoral outcomes offers two additional advantages. First, it enables the comparison of survey results to actual aggregate data.[47] Second, it allows me to study the causal effects of increased inequality on an outcome that has direct policy implications.

All results continue suggesting a positive effect on demand for redistribution. Table B12 studies the effects of the quasi-experiment based on the alternative survey measures. Results from the alternative demand for redistribution question are on par with the baseline, with exposure to a new apartment building increasing demand for redistribution by 0-11% of a SD (up to 5% of the mean). The treatment increases the likelihood to vote for a left-wing party by 1-4% of a SD (0.5-2pp). Table B13 finds additional support to the effect on demand for redistribution by exploiting

[44] Results in the bottom panel are qualitatively and statistically identical when estimating the model by ordered Probit instead of OLS.

[45] The question does not ask nor mention the words "income" or "wealth" explicitly. Instead, it emphasizes words such as "elite", "top", or "base". Gimpelson and Treisman (2018) argues that, because the previous questions in the ISSP survey asked respondents about income or earnings, "an interpretation in terms of income is the most natural one'.' That was also the case in the present survey, and the correlation between *Perceived Gini* and *Perceived Gini (Pyramid)* is positive but small (0.10).

[46] The parties classified as left-wing were: ECP-Podemos, CUP, ERC, and PSC-PSOE.

[47] With the caveat that the translation between individual and aggregate data will not be perfect (King 2013, Robinson 1950).

aggregate electoral data. Results show that treated tracts are more supportive of left-wing parties (4-8% of a SD, 0.3-0.7pp, or 0.5-1% of the mean).[48] Treatment effects on all measures of demand for redistribution are consistently small but also consistently positive.

5.4 Mechanisms and heterogeneity

Perceived income distribution: The effects on perceived inequality are driven by higher perceived income at the top. Table 6 shows that individuals exposed to the treatment perceive significantly higher incomes in the percentiles 90 and 99. The magnitude ranges between 12 and 17% of a SD in these percentiles. The treatment also (non-significantly) increases perceived income in the percentiles 70, 50, and 30 (by 5-8% of a SD). It slightly decreases perceived income in the 10th percentile (-3% of a SD). These results are intuitive as, relative to the existing housing stock, new buildings are on average of a superior value and quality.

Rental status and gentrification: There is no evidence of heterogeneous effects based on rental status. Table 5 looked at differential effects between renters and homeowners, primarily to investigate whether there was residential mobility before or after the rise of new buildings. The tables did not show evidence in this regard. A second reason to look at that particular split (although not previously articulated) was to see whether gentrification could be a relevant driver of the results. If new apartment buildings are associated with gentrification, treated homeowners become relatively wealthier (as dwelling values in the local area increase), and renters become relatively poorer (their wealth is not directly affected, but rental prices are likely to go up). Therefore, the effects could plausibly differ based on rental status. That was not the case, thus suggesting that gentrification is not a primary driver for the results.

Other factors: Effects are slightly stronger among left-wing, low-income, younger, and Spanish-born individuals. I explore heterogeneity along these and other dimensions in Appendix C. The effects on perceived inequality are stronger among individuals that are young, low-income, single, left-wing, and natives (Table C1). Within these groups, treatment effects range between 20 and 30% of a SD (3.5 to 5.3 points in *Perceived Gini*). Looking at the demand for redistribution (Table C2), coefficients are also generally larger in these groups, but differences are not significant.

6 Conclusions

Neighborhoods significantly affect beliefs about inequality. They also (mildly) influence demand for redistribution. Descriptive results suggested that individuals living in more unequal neighborhoods perceived about 4% more national-level inequality but (if anything) were less in favor of redistribution. Residential sorting could explain the latter, perhaps counter-intuitive, pattern. I

[48] A tract is defined as treated if its centroid is within 200 (Columns 1-2), 350 (Columns 3-4), or 500 (Columns 5-6) meters from a new apartment building.

exploited the rise of new apartment buildings as an exogenous shock to local environments and found that exposure to those increased perceived inequality by 7% and demand for redistribution by 1%. Effects were driven by higher perceived income at the top and were slightly larger among young, low-income, left-wing, and Spanish-born individuals.

If policymakers wish to correct misperceptions, local environments are a good starting point. Individuals systematically misperceive inequality. Perceptions are essential drivers of individuals' behavior and decisions. Thus, policymakers may want to correct those, as they could lead to suboptimal policies. Correcting misperceptions is undoubtedly a challenging endeavor, but this work suggests an obvious starting point: local environments. Given that beliefs about inequality are partly determined locally, any campaign trying to correct misperceptions should have a strong local component and target those areas farther away from the *representative* neighborhood (i.e., those that look less like the country as a whole). Misperceptions are likely to be more exacerbated in those places.

Granularity in the data matters. More is needed. The level of detail present in this paper's data allowed me to document a relationship between neighborhoods, perceptions, and preferences for redistribution. A similar level of granularity is necessary to further investigate the effects of local environments on other kinds of perceptions or alternative outcomes plausibly determined at the local level. Unfortunately, publicly available datasets are often too coarse. Thus, this paper is a call to the institutions responsible for disseminating data to, whenever possible, make it available at the most disaggregated level possible.

This paper suggests two lines for future research. First, study whether local environments also influence other kinds of perceptions (e.g., immigration or social mobility). Second, identify the complete set of channels shaping perceptions and quantify their weight. This paper has provided evidence that individuals extrapolated from their local environments when forming their beliefs (at least about inequality). The literature suggests that other channels could also play a role (Diermeier et al. 2017, Enikolopov et al. 2011, Hauser and Norton 2017, Kim 2019, Petrova 2008). Future work should fully characterize those along with their relative importance.

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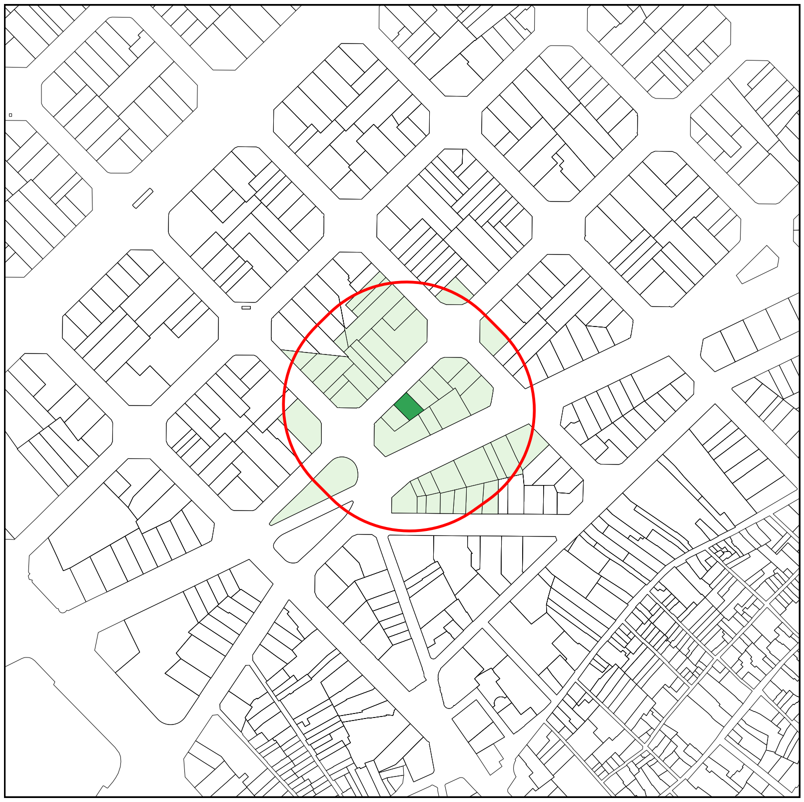


Figure 1: Defining local neighborhoods

Notes: This figure illustrates Step 3 in the Local Neighborhood Gini (LNG) construction algorithm. The local neighborhood (plots colored in light-green) of a building of reference (plot colored in dark-green) is defined as the set of dwellings contained within an r-meter buffer ($r = 100$ in this example) with origin in the apartment building's centroid. See Section 2.3 for the details on the LNG construction process. Cartography from the Eixample district in the city of Barcelona. Source: Spanish Cadastre.

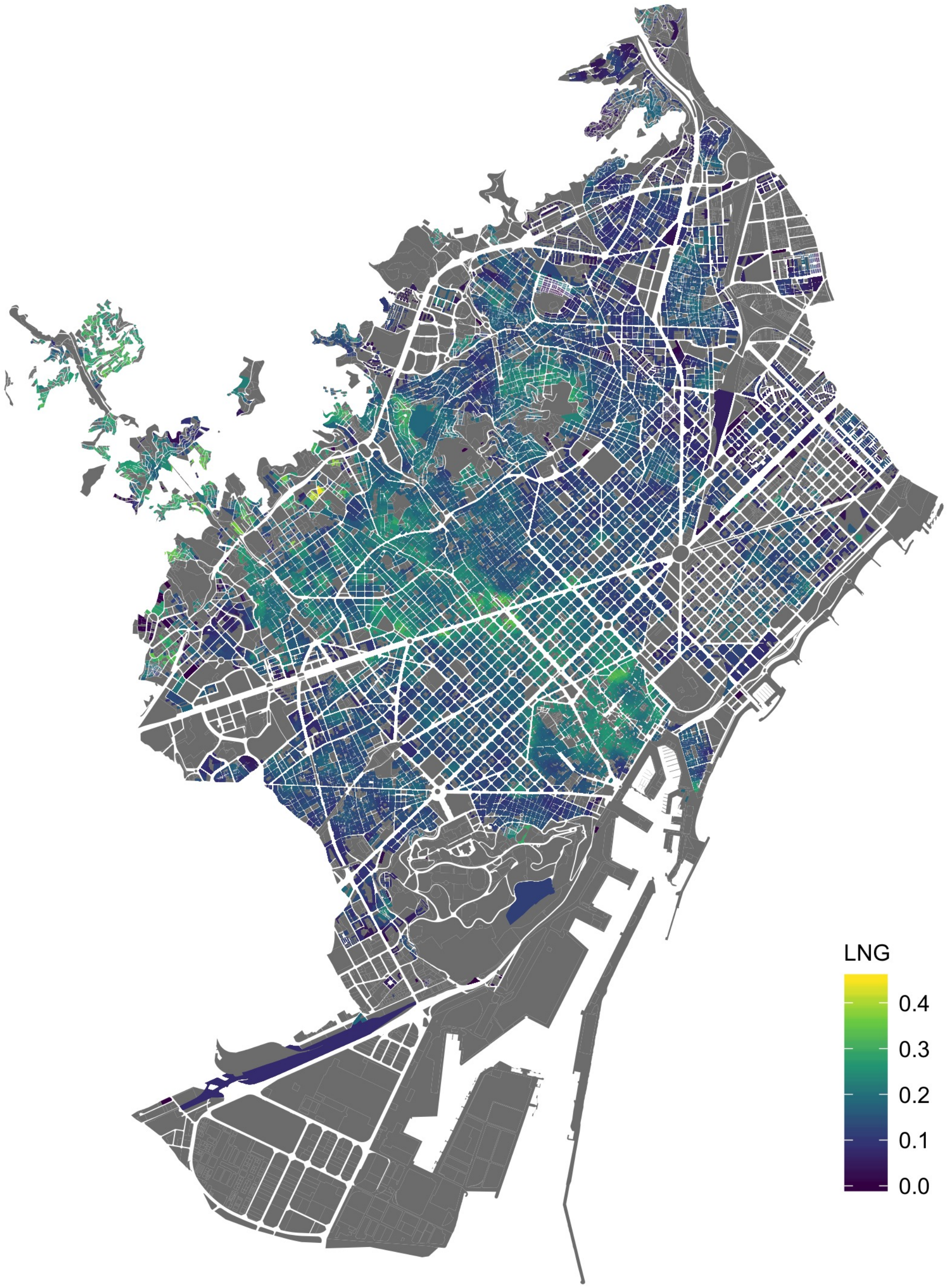


Figure 2: The Local Neighborhood Gini (LNG) in Barcelona ($r = 100$)

Notes: This figure shows the Local Neighborhood Gini (LNG) (dwelling value) in Barcelona ($r = 100$ meters). Lighter-color polygons correspond to plots (apartment buildings) with more unequal local neighborhoods. Darker polygons correspond to apartment buildings with more homogeneous local neighborhoods. Gray polygons correspond to non-residential buildings (e.g., hospitals, office buildings).

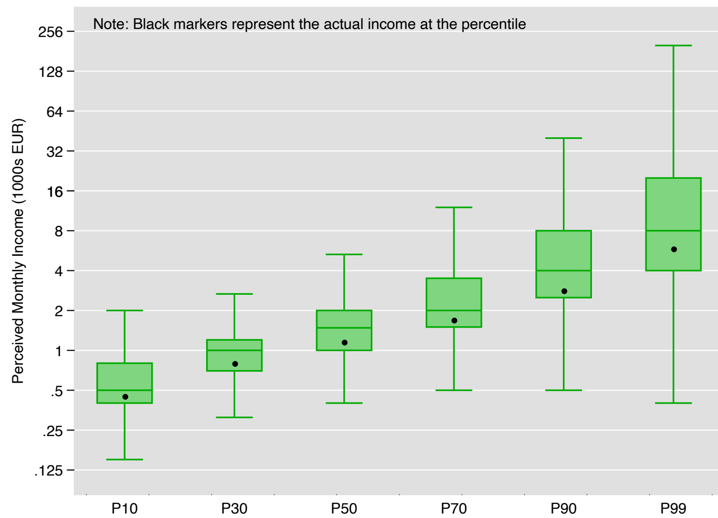


Figure 3: Perceived national income distribution among respondents

Notes: Boxplot of respondents' perceived monthly income at different percentiles. The figure excludes outliers. The y-axis is log-scaled. The median values for the percentiles 10, 30, 50, 70, 90, and 99 were 500, 1000, 1400, 2000, 4000, and 8000, respectively. The actual monthly incomes in these percentiles were 446, 790, 1144, 1678, 2795, and 5791, respectively (ECV, 2018). The black markers in the figure represent these values.

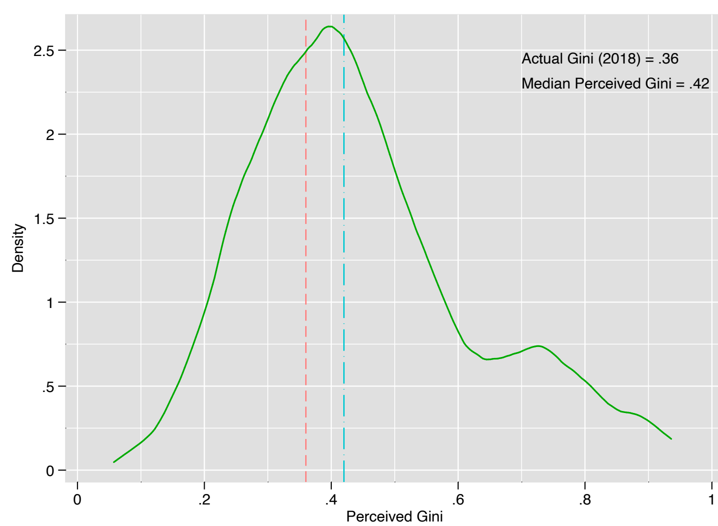


Figure 4: Perceived income inequality among respondents

Notes: This figure shows the distribution of *Perceived Gini* among survey respondents. To construct this variable, I first elicited respondents' perceived national income at the percentiles 10, 30, 50, 70, 90, and 99. I then interpolated to recover the entire distribution. *Perceived Income Gini* is the Gini index of that distribution. The mean value is 0.45. The median is 0.42 (blue-dashed line). The actual Gini (red-dashed line) in 2018 was 0.36 (ECV, 2018).

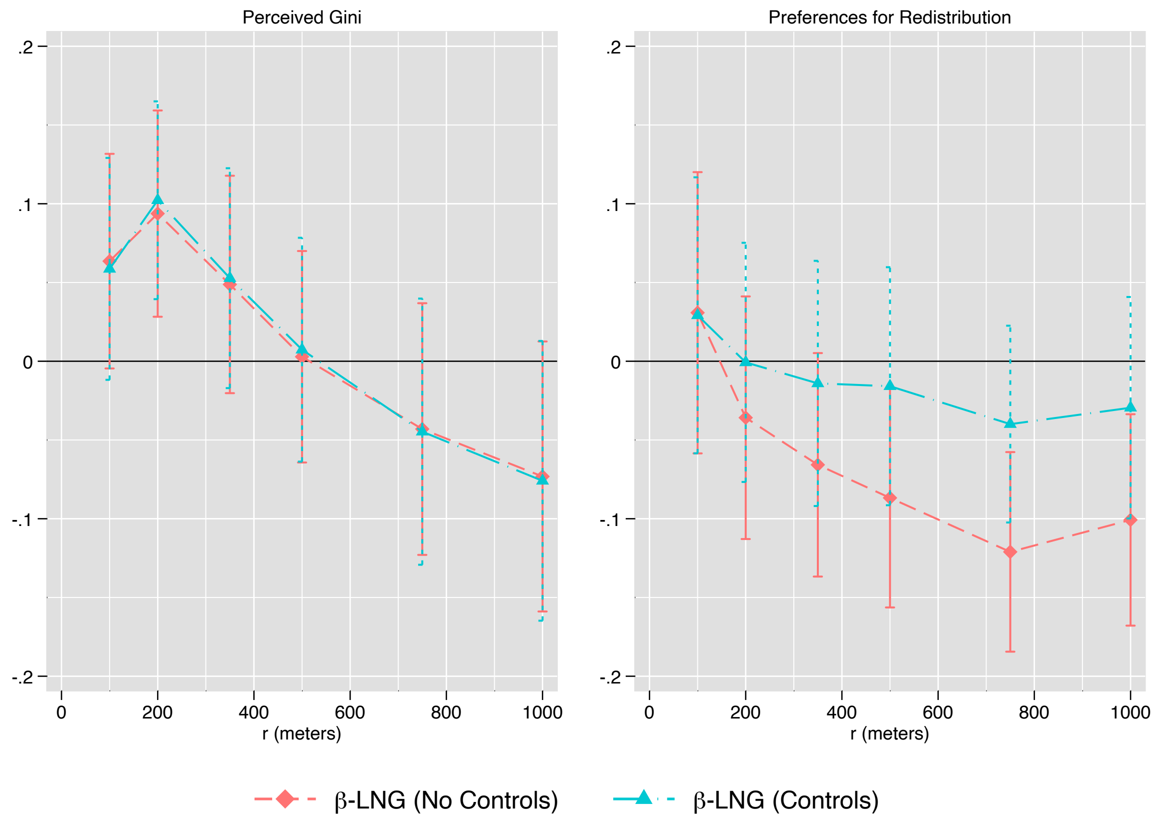


Figure 5: Local inequality (LNG), perceived inequality, and preferences for redistribution

Notes: This figure explores the relationship between local inequality, perceived inequality, and preferences for redistribution. All continuous variables are standardized. Perceived inequality (the outcome on the left panel) is measured with *Perceived Gini*, constructed as described in Section 3.2. *Preferences for Redistribution* (the outcome on the right panel) measures demand for redistribution on a scale from 0 to 10, with 10 representing the highest demand for redistribution. Local inequality is measured using the Local Neighborhood Gini (LNG), which captures inequality in dwelling values in narrowly defined neighborhoods constructed as described in Section 2.3. Each coefficient in the plot is an OLS estimate of β in Equation 1 (with or without controls), with the spatial scope of neighborhoods (characterized by r) varying across the x-axis. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors are clustered at the city-neighborhood level. Vertical bars show 95% confidence intervals.

(a) Year 2012

(b) Year 2015

Figure 6: Example of an "apartment building shock"

Notes: Example of a new apartment building shock. In 2012, the Local Neighborhood Gini (LNG) ($r = 100$) associated with the building in the top panel was 0.02. In 2015, the LNG increased to 0.23 after the construction of a new apartment building on a former parking lot. Building details: C/ Aiguablava 3, 08042 Barcelona (Cadastre code 1690916DF3819B). Images retrieved from Google Maps.

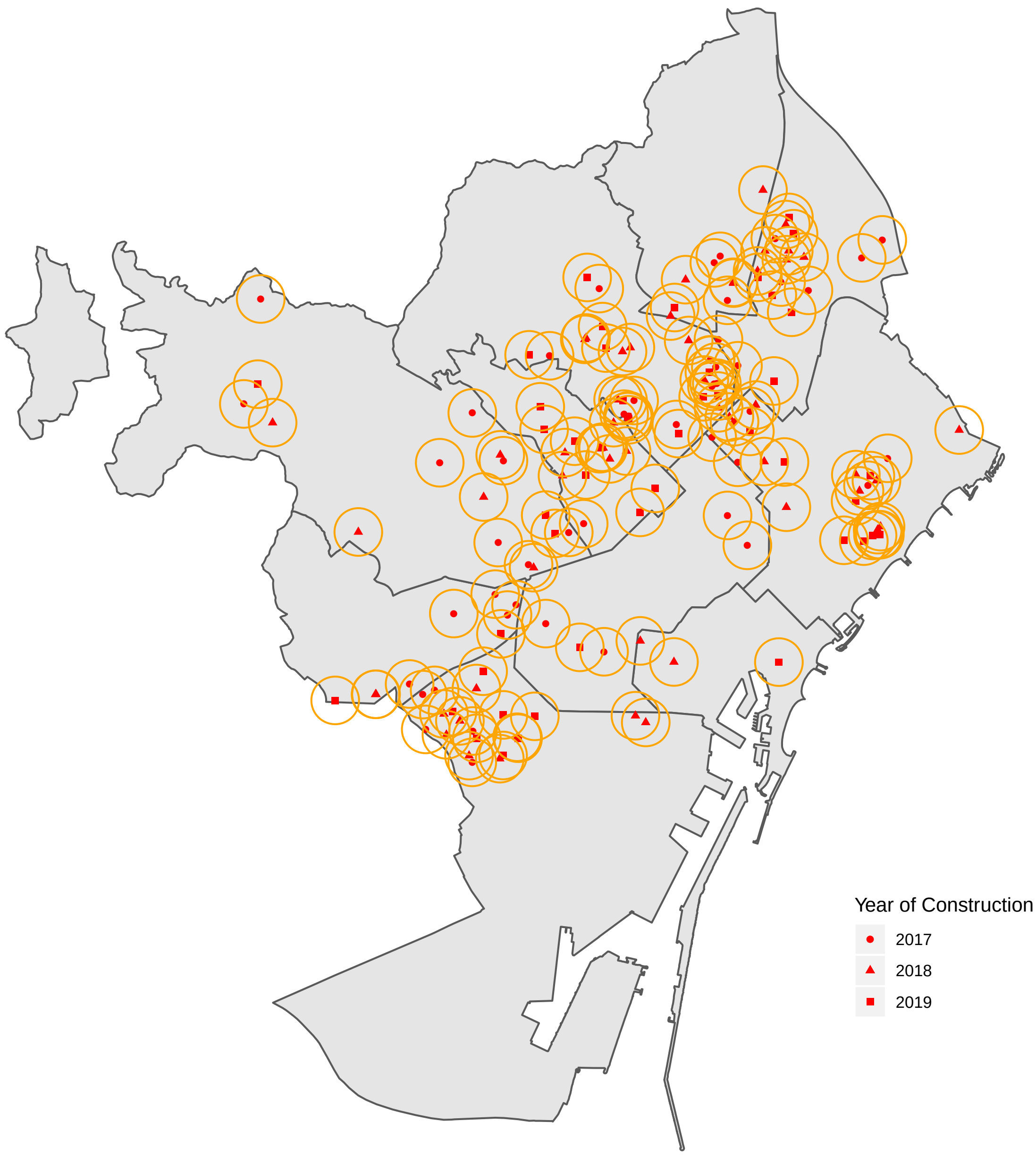


Figure 7: Visualization of the new apartment building identification strategy

Notes: Visualization of the new apartment building identification strategy. The figure shows a map of Barcelona with each of its (10) districts delimited. Red symbols represent new apartment buildings constructed in 2017, 2018, or 2019. Orange circumferences represent 350-meter buffers. The baseline specification compares respondents living in the interior of a buffer (treated) with others residing outside, within the same district. The baseline sample includes individuals that lived in the same dwelling in 2015.

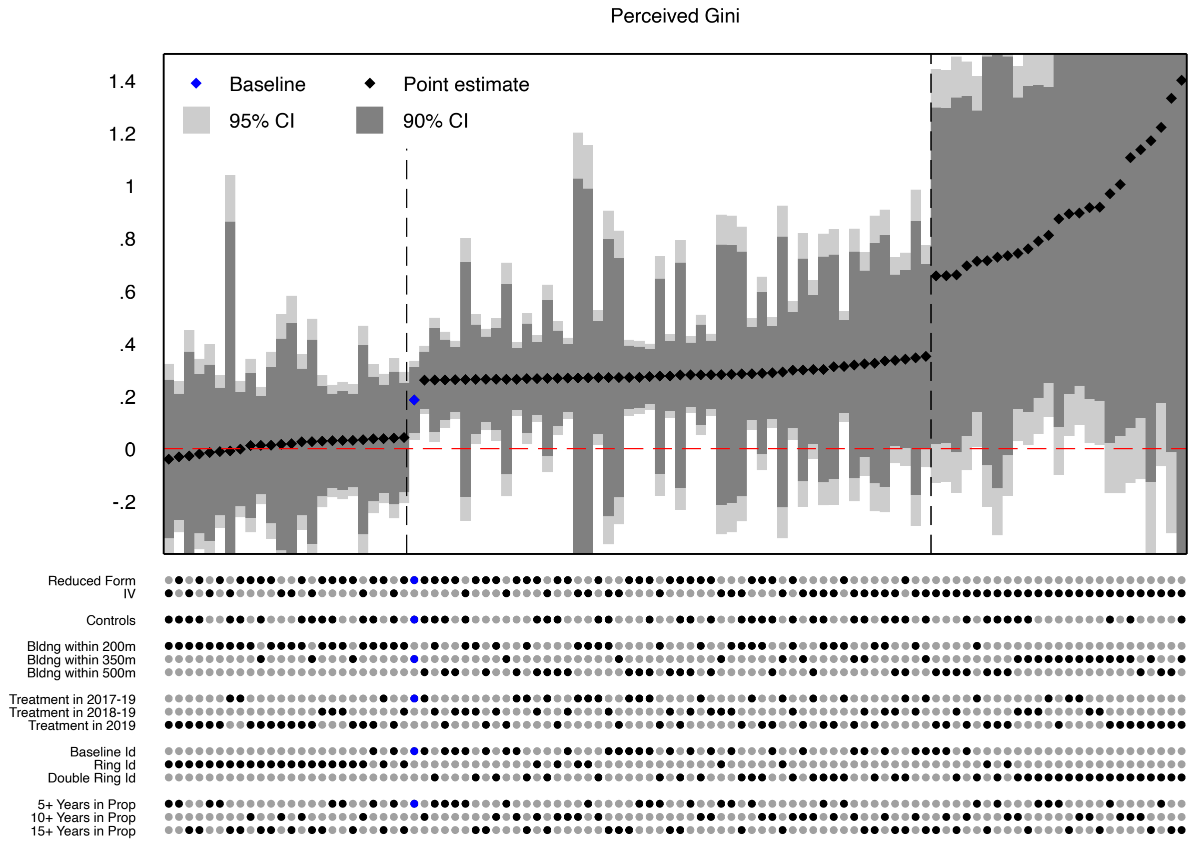


Figure 8: Specification curve: new building treatment and perceived inequality

Notes: This figure summarizes the results of 325 specifications studying the effects of the new building treatment on perceived inequality. For expositional purposes, the figure only includes 100 specifications: the bottom and top 25, along with the 50 in the middle (and the baseline, the marker in blue). All coefficients are standardized and sorted by value. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *New Building Treatment* (in the baseline) is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built in 2017-19). Across specifications, the definition of treatment can vary with distance (200m, 350m, 500m) or with time (building constructed in 2017-19, 2018-19, or 2019). Control individuals are those that are not treated. *Ring Id* and *Double-ring Id* exploit alternative samples for the control group (see Section 5.3 and Figure B2 for details). ΔLNG is instrumented with *New Building Treatment* in *IV* specifications. The sample is restricted to individuals who have resided in the same dwelling since at least 2015 (baseline), 2010, or 2010. Controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. All regressions include city-district fixed effects. The smallest β estimate is -0.04 and the largest is 1.53 (value censored at 1.4 for illustration purposes). Coefficients are positive in 317 specifications and the mean value is 0.34. The baseline value is 0.18 (92nd smallest).

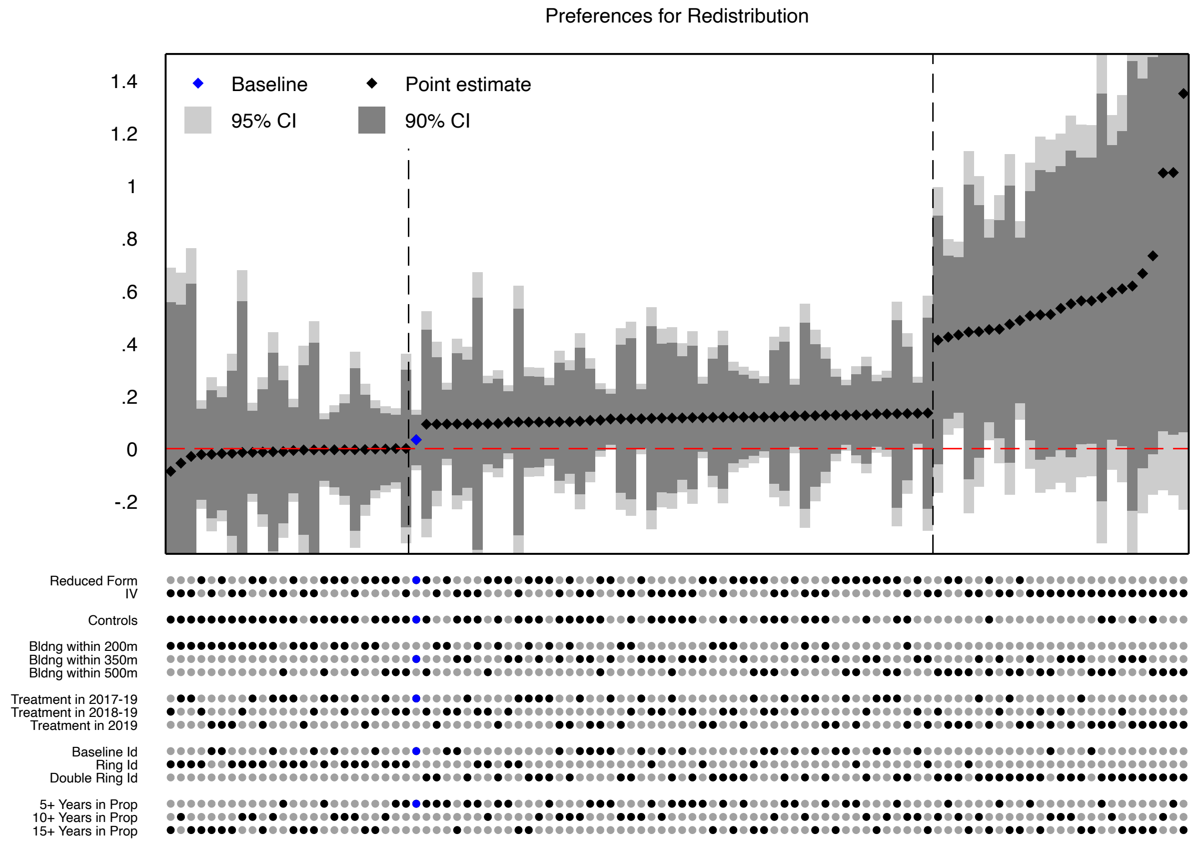


Figure 9: Specification curve: new building treatment and preferences for redistribution

Notes: This figure summarizes the results of 325 specifications studying the effects of the new building treatment on preferences for redistribution. For expositional purposes, the figure only includes 100 specifications: the bottom and top 25, along with the 50 in the middle (and the baseline, the marker in blue). All coefficients are standardized and sorted by value. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* (in the baseline) is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built in 2017-19). Across specifications, the definition of treatment can vary with distance (200m, 350m, 500m) or with time (building constructed in 2017-19, 2018-19, or 2019). Control individuals are those that are not treated. *Ring Id* and *Double-ring Id* exploit alternative samples for the control group (see Section 5.3 and Figure B2 for details). ΔLNG is instrumented with *New Building Treatment* in *IV* specifications. The sample is restricted to individuals who have resided in the same dwelling since at least 2015 (baseline), 2010, or 2010. Controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. All regressions include city-district fixed effects. The smallest β estimate is -0.09 and the largest is 1.35. Coefficients are positive in 303 specifications and the mean value is 0.16. The baseline value is 0.03 (50th smallest).

Table 1: Survey representativity

	Sample	Barcelona	Difference
Female	0.461	0.532	-0.071
	(0.015)		
Age	46.262	50.316	-4.055
	(0.430)		
Married	0.465	0.479	-0.014
	(0.015)		
Foreign Born	0.076	0.304	-0.227
	(0.008)		
University	0.629	0.328	0.301
	(0.014)		
Renter	0.418	0.382	0.036
	(0.015)		
Unemployed	0.098	0.110	-0.012
	(0.009)		
HH Income (1000s EUR)	47.384	51.539	-4.155
	(1.157)		
HH Size	2.666	2.360	0.306
	(0.033)		
Voted a Left-wing Party	0.746	0.635	0.110
	(0.013)		
Voted a Right-wing Party	0.210	0.328	-0.118
	(0.012)		
N	1330	1404407	

Notes: This table compares the characteristics of the survey sample with those from the target population (i.e., adults residing in Barcelona). The population figures for Female, Age, and Foreign-Born were obtained from the 2020 Municipal Registry (INE). Marriage and High-education statistics were obtained from the 2011 Census. Renter statistics were obtained from the Barcelona City Council. Unemployment figures were obtained from the National Employment Agency (SEPE). Household Income and Household Adults were obtained from the 2017 INE Atlas de Renta. Electoral outcomes were obtained from the Ministry of the Interior. Standard errors in parentheses.

Table 2: The determinants of perceived inequality and preferences for redistribution

	Perceived Gini		Pref for Redistribution		
	(1)	(2)	(3)	(4)	(5)
Perceived Gini					0.142
					(0.028)
Female	-0.160	-0.167	0.007	0.003	0.027
	(0.058)	(0.059)	(0.058)	(0.058)	(0.062)
Age	0.020	0.014	0.007	0.008	0.006
	(0.041)	(0.041)	(0.030)	(0.031)	(0.030)
Married	-0.097	-0.101	0.066	0.068	0.083
	(0.061)	(0.063)	(0.053)	(0.054)	(0.052)
Foreign Born	-0.063	-0.046	-0.127	-0.135	-0.129
	(0.087)	(0.089)	(0.081)	(0.085)	(0.085)
University	0.275	0.246	0.102	0.106	0.071
	(0.066)	(0.061)	(0.047)	(0.049)	(0.048)
Renter	0.069	0.046	0.099	0.093	0.086
	(0.064)	(0.064)	(0.056)	(0.054)	(0.056)
Unemployed	0.099	0.109	0.133	0.131	0.116
	(0.095)	(0.095)	(0.077)	(0.080)	(0.078)
Log HH Income	0.062	0.063	0.066	0.071	0.062
	(0.026)	(0.026)	(0.024)	(0.025)	(0.025)
HH Size	0.012	0.004	-0.069	-0.067	-0.067
	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)
Religious	-0.088	-0.093	-0.197	-0.187	-0.174
	(0.069)	(0.069)	(0.061)	(0.061)	(0.060)
Left-wing	0.247	0.255	0.784	0.782	0.746
	(0.066)	(0.068)	(0.058)	(0.060)	(0.061)
Dep Var Mean (Non-std)	0.447	0.447	6.565	6.565	6.565
Dep Var SD (Non-std)	0.178	0.178	2.339	2.339	2.339
R2	0.052	0.057	0.185	0.191	0.210
N	1330	1330	1330	1330	1330
District FE		X		X	X

Notes: This table explores the determinants of perceived inequality and distributional preferences. All continuous variables are standardized. *Perceived Gini* measures the participant perceptions of local inequality from respondents' perceived income distribution, as described in Section 3.2. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table 3: Local inequality (LNG), perceived inequality, and preferences for redistribution

	Perceived Gini											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG	0.064	0.094	0.049	0.003	-0.043	-0.073	0.062	0.104	0.054	0.008	-0.045	-0.075
	(0.034)	(0.033)	(0.035)	(0.034)	(0.040)	(0.043)	(0.036)	(0.032)	(0.035)	(0.035)	(0.042)	(0.044)
Dep Var Mean (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
R2	0.010	0.012	0.008	0.007	0.008	0.009	0.057	0.060	0.056	0.055	0.056	0.057
	Preferences for Redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG	0.031	-0.036	-0.066	-0.087	-0.121	-0.101	0.033	0.001	-0.013	-0.015	-0.042	-0.030
	(0.045)	(0.039)	(0.036)	(0.035)	(0.032)	(0.034)	(0.044)	(0.039)	(0.039)	(0.037)	(0.031)	(0.035)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339
R2	0.012	0.012	0.013	0.014	0.017	0.015	0.186	0.185	0.185	0.185	0.186	0.185
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table explores the relationship between local inequality, perceived inequality (top panel), and preferences for redistribution (bottom panel). All continuous variables are standardized. Perceived inequality is measured with *Perceived Gini*, constructed as described in Section 3.2. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Local inequality is measured using the Local Neighborhood Gini (LNG), which captures inequality in dwelling values in narrowly defined neighborhoods, constructed as described in Section 2.3. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table 4: New apartment building treatment and local inequality

	Δ LNG (Value)			Δ LNG (Space)		
	(1)	(2)	(3)	(4)	(5)	(6)
New Building Treatment (200m)	0.074 (0.109)			0.394 (0.129)		
New Building Treatment (350m, baseline)		0.081 (0.148)			0.331 (0.105)	
New Building Treatment (500m)			0.067 (0.226)			0.454 (0.164)
r (meters)	200	350	500	200	350	500
Dep Var Mean (Non-std)	-0.123	-0.124	-0.120	0.002	0.002	0.002
Dep Var SD (Non-std)	0.114	0.090	0.079	0.012	0.008	0.005
R2	0.302	0.429	0.477	0.077	0.115	0.204
N	1330	1330	1330	1330	1330	1330
District FE	X	X	X	X	X	X

Notes: This table shows the effects of the new apartment building treatment on local inequality. All continuous variables are standardized. The dependent variable is the percentage change in LNG during 2016-19 in either dwelling value (Columns 1-3) or dwelling space (Columns 4-6). *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 200, 350, or 500 meters of a new apartment building (constructed in 2017-19). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table 5: New apartment building treatment, perceived inequality, and preferences for redistribution

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.212	0.185	0.229	0.210	0.203	0.162	0.170	0.157	0.220	0.175
	(0.073)	(0.075)	(0.075)	(0.081)	(0.086)	(0.089)	(0.136)	(0.109)	(0.082)	(0.087)
Dep Var Mean (Non-std)	0.441	0.441	0.435	0.435	0.436	0.436	0.449	0.449	0.437	0.437
Dep Var SD (Non-std)	0.176	0.176	0.173	0.173	0.176	0.176	0.177	0.177	0.176	0.176
R2	0.017	0.070	0.019	0.071	0.018	0.066	0.035	0.156	0.021	0.062
	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.112	0.034	0.113	0.045	0.132	0.058	0.038	0.063	0.151	0.011
	(0.058)	(0.057)	(0.067)	(0.071)	(0.074)	(0.074)	(0.107)	(0.104)	(0.077)	(0.076)
Dep Var Mean (Non-std)	6.487	6.487	6.403	6.403	6.418	6.418	6.771	6.771	6.352	6.352
Dep Var SD (Non-std)	2.311	2.311	2.295	2.295	2.244	2.244	2.294	2.294	2.308	2.308
R2	0.012	0.176	0.022	0.180	0.025	0.150	0.015	0.164	0.023	0.201
N	937	937	704	704	586	586	301	301	636	636
Indiv Controls		X		X		X		X		X
N'hood Controls		X		X		X		X		X
District FE	X	X	X	X	X	X	X	X	X	X
Years in Dwelling	5+	5+	10+	10+	15+	15+	5+	5+	5+	5+
Sample	Full	Full	Full	Full	Full	Full	Renters	Renters	Owners	Owners

Notes: This table shows the effects of the new apartment building treatment on perceived inequality (top panel), and preferences for redistribution (bottom panel). All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Columns 3-6 further restrict the sample to individuals who have lived same dwelling since at least 2010 or 2005. Columns 7-10 further restrict the sample to include only either renters or homeowners. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table 6: New apartment building treatment and perceived income

	Perceived P99		Perceived P90		Perceived P70		Perceived P50		Perceived P30		Perceived P10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
New Building Treatment	0.224	0.200	0.187	0.165	0.122	0.109	0.106	0.101	0.094	0.087	-0.002	-0.015
	(0.073)	(0.067)	(0.071)	(0.070)	(0.068)	(0.067)	(0.069)	(0.067)	(0.065)	(0.063)	(0.069)	(0.067)
Dep Var Mean (Non-std)	9.151	9.151	8.360	8.360	7.710	7.710	7.241	7.241	6.800	6.800	6.143	6.143
Dep Var SD (Non-std)	1.856	1.856	1.459	1.459	1.240	1.240	1.133	1.133	1.116	1.116	1.360	1.360
R2	0.027	0.118	0.022	0.107	0.018	0.105	0.019	0.108	0.017	0.110	0.010	0.098
N	937	937	937	937	937	937	937	937	937	937	937	937
Indiv Controls		X		X		X		X		X		X
N'hood Controls		X		X		X		X		X		X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows the effects of the new apartment building treatment on perceived income. All continuous variables are standardized. *Perceived P99*, *Perceived P90*, *Perceived P70*, *Perceived P50*, *Perceived P30*, and *Perceived P10* denote perceived log income at a given percentile. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Web Appendix of
Neighborhoods, Perceived Inequality, and Preferences for Redistribution: Evidence from Barcelona

Gerard Domènech-Arumí

A The Local Neighborhood Gini: additional details

A.1 The spatial distribution could matter: intuition

Local inequality could be a critical determinant of inequality perceptions. To illustrate this point, consider the two abstract cities depicted in Figure A1. Each polygon represents a dwelling. The number in its interior represents the value (or size). Note that both cities contain exactly four large/high-value dwellings and eight small/low-value dwellings, with values of 100 and 50, respectively. Therefore, any measure of inequality will describe both cities as unequal. For example, a standard Gini index yields a value of 0.167. Let us now look at the two dwellings colored in dark green at both cities' eastern borders. They both have the same value/size (50) and are located in equivalent coordinates within their respective cities. However, the disparity in the composition of their respective local neighborhoods (dwellings in light-green) is apparent. While all the neighboring dwellings in City 1 are of the same value, those in City 2 are not. This Gini index of the two dwellings' local neighborhoods — with values of 0 and 0.167 in City 1 and 2, respectively — makes this point clear.

Now suppose that households were immobile and isolated from others in the rest of the city. Suppose interactions were limited to only the closest neighbors. In that scenario, it is reasonable to think that each dwelling's local neighborhood plays a significant role in determining inequality perceptions. Citywide inequality would not be that relevant, as households could only know about other households through interactions with their closest neighbors. Of course, in reality, individuals are not immobile, and they interact with others outside their immediate neighborhood. However, as long as they spend some fraction of their time at home,[1] or as long as interactions of some form occur at the neighborhood level, the previously outlined mechanism should play some role.[2]

A.2 Dwelling value estimation

I used the Ranger package in R to implement Breiman (2001)'s Random Forest algorithm and predict the (log) price of each dwelling in Barcelona.[3] The prediction used the roughly 65,000 real estate transactions that took place in Barcelona in 2009-19, combined with all the information from the census, registry, and other sources — 157 variables in total.[4] The prediction error (Out of Bag Root Mean Squared Error, OOBRMSE) of

[1]Using mobile phone data, Athey et al. (2020) report that an average American spends about 40% of their time at home.

[2]Evidence suggests that interactions at the local level matter. For example, Wellman (1996), in the context of Toronto, shows that close neighbors account for a significant share of contacts. Bayer et al. (2008), in the context of Boston, shows that interactions at the city-block level can have positive effects in the marketplace, for example, in terms of job referrals.

[3]Several studies suggest that random forests typically overperform standard hedonic price regressions and other machine learning methods such as LASSO (Čeh et al. 2018, Fan et al. 2006, Mullainathan and Spiess 2017).

[4]I implemented the algorithm using hyperparameter tunning (sample split, variables per split, nodes). The final prediction grew 500 trees, nine nodes, an 80% sample split, 42 variables to split in each node, and allowing the algorithm to decide on each variable's importance based on the reduction of node impurity after each split.

the algorithm was 0.1437.[5] The most important variable for the prediction (by a magnitude of almost 3) was dwelling size (square meters). Other variables with high relevance in the prediction included the median income in the census tract, the median selling price per square meter at the district level, the transaction year, the quality of the apartment, and the year of construction.

A.3 The LNG compared to income inequality in Spanish cities

Table A1 provides a comparison between different inequality measures defined at the city level (whenever possible). In that table, *Income Gini* is the standard Gini coefficient obtained from the 2018 *Encuesta de Condiciones de Vida* (ECV) microdata.[6] The measure reflects pre-tax income inequality in 2018, the latest available in the data. Citywide *Value* and *Space Gini* reflect the dispersion in predicted dwelling values and actual dwelling space across the city. Mean LNG (Value and Space) reflect the mean LNG ($r = 100$) across city dwellings. *Value Gini* and *Mean LNG (Value)* are only available for Barcelona as that is the only city in the sample covered by the ATC data.

Pre-tax income inequality is high in these cities' regions, and always above Value Gini (in Barcelona) and Space Gini. At least three reasons could explain this. First, income is likely to exhibit higher variance than dwelling sizes (and therefore possibly dwelling values too). Second, space is scarce in cities, even when it is possible to increase density (e.g., by building taller buildings). Third, preferences over housing consumption are likely to be non-homothetic. Those at the top might be more prone to invest in assets other than real estate once a certain amount of dwelling consumption is attained (Albouy et al. 2016, Couture et al. 2019, Yang 2009).

Citywide value/space inequality is above the mean LNG. It is helpful to go back to the toy example in Figure A1 to interpret this result. Both cities have a City Gini of 0.167, but they substantially differ in their mean LNG. The mean LNG in City 2 is 0.161. It is 0.091 in City 1 (about 43% smaller). The large discrepancy is due to the differential spatial distribution of dwellings within the city or, in other words, due to differences in residential segregation. As Glaeser et al. (2009) articulated, local inequality and segregation are essentially two sides of the same coin. Hence, even if not formally defined in this paper, the gap between city Gini and mean LNG is informative about the level of housing segregation in the city.

[5]Other studies predicting house values have achieved OOBRMSEs of 0.12-0.16 (Čeh et al. 2018, Fan et al. 2006, Mullainathan and Spiess 2017). The performance of my prediction lies in the middle range of those. The slight underperformance could be a consequence of not using the number of rooms (a variable with typically high explanatory power) for the prediction (as it is not available).

[6]The ECV is part of the Luxembourg Income Study (LIS).

Figure A1: Neighborhood Inequality can substantially differ from city inequality

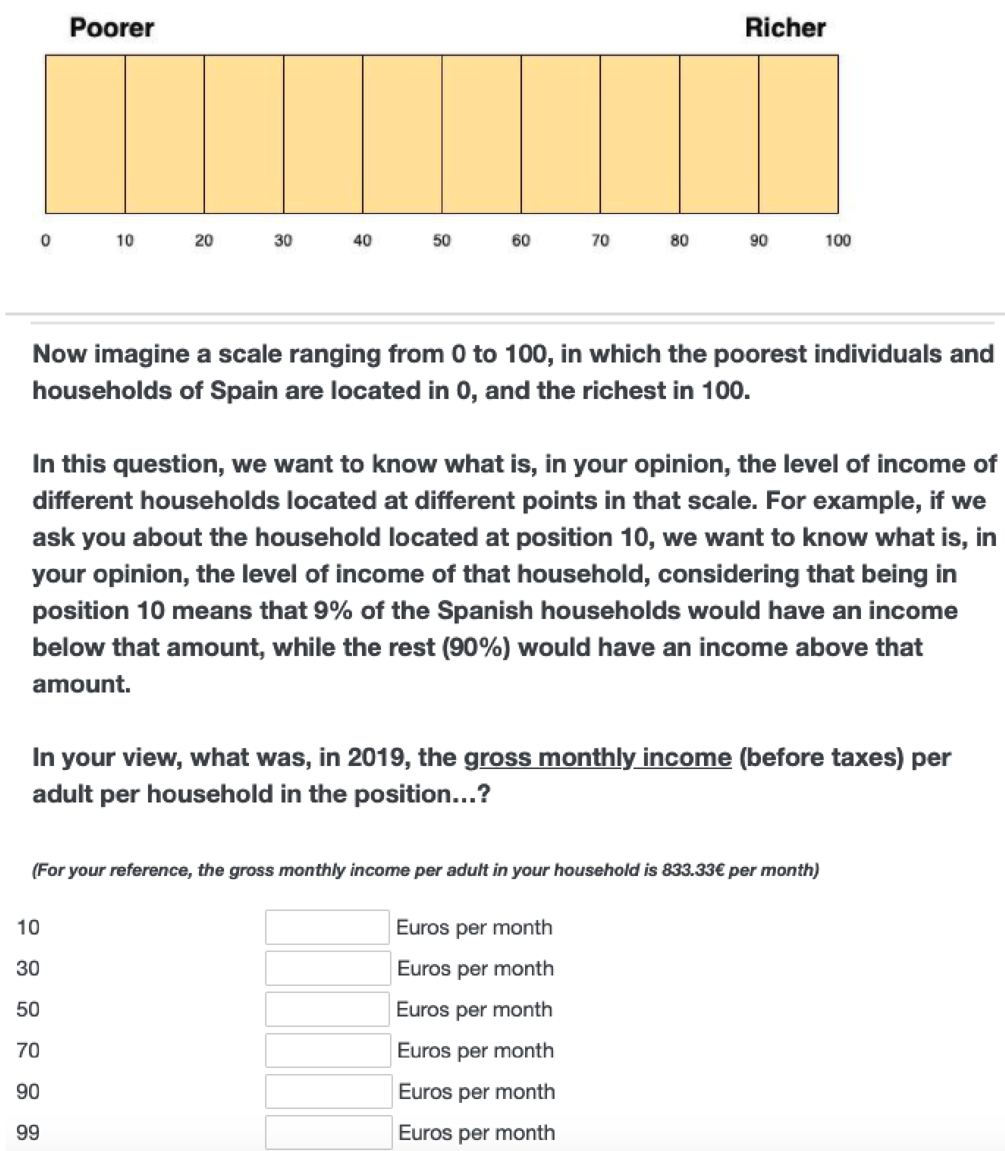
Notes: This figure shows that citywide inequality can substantially differ from local (neighborhood) inequality. The figure shows two abstract cities with different spatial distributions of dwellings, in which each polygon within a city represents a dwelling of different value or size. Both cities have a citywide level inequality (measured using a Gini coefficient) of 0.167 — as both contain exactly four "big" dwellings and eight "small" dwellings that are identical. Due to the differential spatial distribution of dwellings within cities, the mean local inequality (here defined as the mean of the 12 local Gini coefficients that can be computed for each "local neighborhood" in the city) differs. The value is 0.091 in City 1; 0.161 in City 2.

Table A1: Comparison of different inequality measures in Spanish cities

City	Population (City)	Income Gini (Region)	Value Gini (Dwelling Value)	Mean LNG (Value, $r = 100$)	Space Gini (Dwelling Space)	Mean LNG (Space, $r = 100$)
Madrid	3,266,126	0.389	NA	NA	0.255	0.172
Barcelona	1,636,762	0.354	0.295	0.144	0.235	0.176
Valencia	794,288	0.376	NA	NA	0.186	0.146
Sevilla	688,592	0.409	NA	NA	0.235	0.155
Zaragoza	674,997	0.319	NA	NA	0.215	0.150
Murcia	453,258	0.375	NA	NA	0.246	0.155
Palma Mallorca	416,065	0.379	NA	NA	0.255	0.207
Las Palmas	379,925	0.405	NA	NA	0.279	0.186

Notes: This table compares different inequality measures across several Spanish cities. Population is obtained from the 2019 Municipal Registry (INE). (Pre-tax) Income Gini is calculated from the 2018 *Encuesta de Condiciones de Vida* (ECV) microdata, the latest available. Gini calculated at the region level. Citywide Value Gini (only available for Barcelona) captures the dispersion in predicted dwelling values in the city (see Section A.2 for the estimation details). Mean Local Neighborhood Gini (LNG) (Value) is the mean Local Neighborhood Gini (LNG) capturing dispersion in dwelling value in the city (only available for Barcelona). Citywide Space Gini is the Gini index capturing dispersion in dwelling sizes (square meters) in the city. Mean LNG (Space) is the mean LNG capturing dispersion in dwelling size in the city.

B Additional figures and tables



Poorer

Richer

0 10 20 30 40 50 60 70 80 90 100

Now imagine a scale ranging from 0 to 100, in which the poorest individuals and households of Spain are located in 0, and the richest in 100.

In this question, we want to know what is, in your opinion, the level of income of different households located at different points in that scale. For example, if we ask you about the household located at position 10, we want to know what is, in your opinion, the level of income of that household, considering that being in position 10 means that 9% of the Spanish households would have an income below that amount, while the rest (90%) would have an income above that amount.

In your view, what was, in 2019, the gross monthly income (before taxes) per adult per household in the position...?

(For your reference, the gross monthly income per adult in your household is 833.33€ per month)

10 Euros per month

30 Euros per month

50 Euros per month

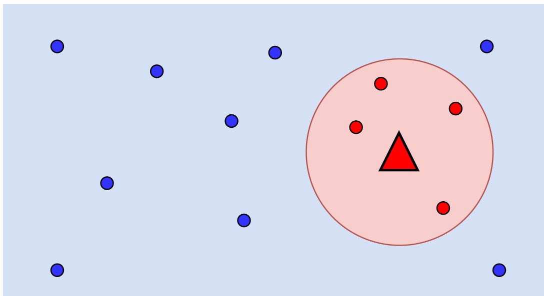
70 Euros per month

90 Euros per month

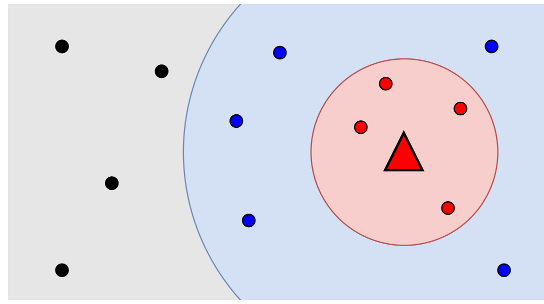
99 Euros per month

Figure B1: Screenshot of the question eliciting respondents' perceived income distribution

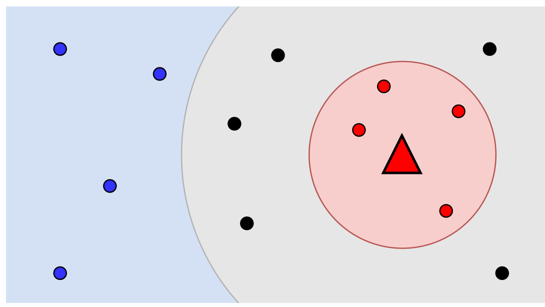
Notes: This figure shows a screenshot of the (translated) survey question designed to measure the perceived income distribution of respondents. Prior to this question, the participant is asked about his or her household income and about his or her perceived relative position in the national income distribution. These earlier questions serve to explicitly define income and introduce the notion of an income distribution.



(a) Baseline identification



(b) Ring identification

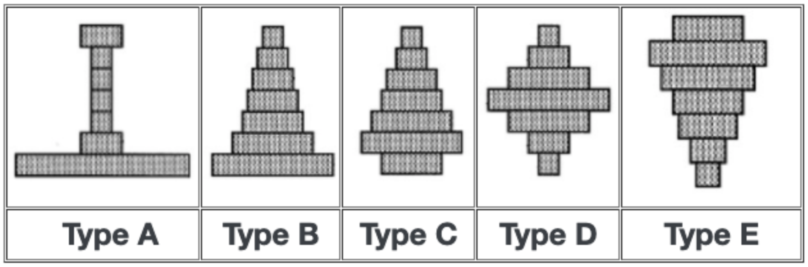


(c) Double ring identification

Figure B2: New apartment building treatment: illustration of alternative identification strategies

Notes: This figure illustrates the different identification strategies followed in Section 5.3: the Baseline Identification (in Panel (a)), the Ring Identification (in Panel (b)), and the Double ring Identification (in Panel (c)). Each subfigure represents a district in Barcelona. The red triangle close to the eastern border represents a new construction. The small circumferences scattered around the polygon represent individual dwellings from the sample located at different district points. The color of these smaller circumferences denotes treatment and sample inclusion status: red for treated, blue for control, and black for exclusion from the sample. The large circumference surrounding the triangle represents the treatment area (e.g., a buffer with a radius of 350 meters). Individuals outside this area are either used as controls (if located in a light-blue area) or left out of the sample (if located in a gray area). The Ring Identification's motivation in (Panel (b)) starts from the idea that individuals residing far away from the new construction might differ in unobservables. Therefore, excluding them would increase sample comparability. The motivation for the Double ring Identification (Panel (c)) arises from the idea that, in the presence of spillovers, control individuals residing "too close" to the treatment area might also be treated and hence bias the treatment effects estimates downwards.

These five diagrams show different types of society. Please read the descriptions and look at the diagrams and decide which you think best describes Spain.



What type of society is Spain? Which diagram best describes Spain currently?

- ○ **Type A.** A small elite at the top, very few people in the middle and the great mass of people at the bottom.
- ○ **Type B.** A society like a pyramid with a small elite at the top, more people in the middle, and most at the bottom.
- ○ **Type C.** A pyramid except that just a few people are at the bottom.
- ○ **Type D.** A society with most people in the middle.
- ○ **Type E.** Many people near the top, and only a few near the bottom.

Figure B3: Screenshot of the alternative question eliciting inequality perceptions, borrowed from the ISSP (2009)

Notes: This figure is a screenshot of the (translated) "pyramid question", first introduced in a survey by the Social Survey Programme (ISSP) in 2009. It serves as an alternative to the question illustrated in Figure 1 to elicit respondents' perceived inequality. It confronts participants with five diagrams representing hypothetical societies and asks them to choose the one that best represents Spain in their view.

Table B1: Sample distribution across the (10) districts and (73) neighborhoods of Barcelona, compared to actual population

District	Neighborhood	Sample (%)	Pop. (%)	District	Neighborhood	Sample (%)	Pop. (%)
Ciutat Vella	El Raval	3.5	3.5	Horta-Guinardó	La Teixonera	0.4	0.9
	El Gòtic	1	1.4		Sant Genís Agudells	0.4	0.5
	La Barceloneta	1.3	1.1		Montbau	0.1	0.4
l'Eixample	Sant Pere	2.6	1.7		La Vall d'Hebron	0.6	0.3
	El Port Pienc	1.1	2.4		La Clota	0.2	0.2
	La Sagrada Família	2.9	3.8		Horta	1.5	2
	la Dreta de l'Eixample	2.6	3.2	Nou Barris	Vilapicina	2.6	1.9
	Antiga Esquerra Eixample	2.2	3.1		Porta	3	1.9
	Nova Esquerra Eixample	3.2	4.3		El Turó de la Peira	0.4	1.2
Sants-Montjuïc	Sant Antoni	2.4	2.8		Can peguera	0.2	0.2
	El Poble Sec	4.7	2.9		La Guineueta	0.8	1.1
	La Marina Prat Vermell	0.2	0.1		Canyelles	0.2	0.5
	La Marina de Port	3.2	2.4		Les Roquetes	0.5	1.2
	la Font de la Guatlla	1.2	0.6		Verdun	0.2	0.9
	Hostalfrance	1	1.2		La Prosperitat	2	2
	La Bordeta	1.1	1.4		La Trinitat Nova	0.5	0.6
	Sants-Badal	1.4	1.8		Torre Baró	0.3	0.2
	Sants	2.2	3.1		Ciutat Meridiana	0.8	0.8
Les Corts	Les Corts	1.5	3.4		Vallbona	0.1	0.1
	La Maternitat	1.3	1.7	Sant Andreu	La Trinitat Vella	0.7	0.8
	Pedralbes	0.3	0.9		Baró de Viver	0.1	0.2
Sarrià-Sant Gervasi	Vallvidrera	0.2	0.3		El Bon Pastor	0.6	1
	Sarrià	1.3	1.8		Sant Andreu	4.6	4.2
	Les Tres Torres	0.7	1.2		La Sagrera	2.3	2.2
	Sant Gervasi-Bonanova	2.6	1.9		El Congrés i els Indians	1.1	1.1
	Sant Gervasi-Galvany	3.5	3.5		Navas	2.1	1.6
Gràcia	El Putget i Farró	2.6	2.2	Sant Martí	El Camp de l'Arpa	2.4	2.8
	Vallcarca	0.9	1.2		El Clot	0.9	2
	El Coll	0.5	0.5		Llacuna del Ploblenou	0.7	1.1
	La Salut	0.5	1		Vila Olímpica	0.2	0.7
	Vila de Gràcia	2.6	3.7		El Poblenou	2	2.5
Horta-Guinardó	El Camp d'en Grassot	2	2.6		Diagonal Mar	0.6	1
	Baix Guinardó	1.2	1.9		El Besòs i el Maresme	0.7	1.8
	Can Baró	0.5	0.7		Provençals Poblenou	0.9	1.5
	El Guinardó	2.3	2.7		Sant Martí Provençals	1.4	1.9
	La Font d'en Farues	0.4	0.7		La Verneda i la Pau	0.8	2.1
	El Carmel	1.3	2.4				

Notes: The table shows the distribution of the survey sample across the ten districts and 73 neighborhoods of Barcelona compared to that of the actual population. Netquest (the company in charge of recruiting participants) was instructed to sample respondents from all districts and neighborhoods while maintaining balance in terms of gender, age, and socio-economic status to the extent possible. Source: 2019 INE Municipal Registry.

Table B2: Other drivers of preferences for redistribution

	Preferences for Redistribution						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perceived Gini	0.142						0.117
	(0.028)						(0.029)
Perceived Immigration		-0.088					-0.061
		(0.027)					(0.026)
Perceived Upward Mobility			-0.114				-0.074
			(0.030)				(0.033)
Perceived Lack of Mobility				0.095			0.051
				(0.027)			(0.031)
Luck					0.029		0.003
					(0.028)		(0.029)
Trust in Politicians						0.023	0.038
						(0.029)	(0.029)
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339
R2	0.210	0.198	0.203	0.200	0.192	0.192	0.225
N	1330	1330	1330	1330	1330	1330	1330
Controls	X	X	X	X	X	X	X
District FE	X	X	X	X	X	X	X

Notes: This table explores some of the major determinants of distributional preferences according to the literature. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *Perceived Immigration* is obtained from *"What share of the population in Spain do you think are immigrants?"*. *Perceived Lack of Mobility* and *Perceived Upward Mobility* measure social mobility perceptions and they are generated from the following question: *"Now think of a child born in a very poor household, among the 20% poorest households in the country. (1) What do you think is the probability that this child, after growing up and forming a family, will still be part of the 20% poorest households in the country?; (2) What do you think is the probability that this child, after growing up and forming a family, will become part of the 20% richest households in the country?"*. *Luck* also measures beliefs about social mobility and is generated from *Some people think that economic status depends almost exclusively on effort, education and professional value (on a scale from 0 to 10, these people would be at 0). Other people think that what really matters is the family origin, connections or simply luck (these people would be at 10 on the scale). In your opinion, what is the most important factor determining economic status in Spain?*. *Trust in politicians* is obtained from *On a scale from 0 to 10, where 0 means "no trust at all" and 10 means "absolute trust", to what extent do you trust in politicians in general?*. Controls include Age, log Household Income, and indicators for Female, University, Marital Status, Religiosity, Left-wing Ideology, Rental Status, Employment Status. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B3: Local inequality and residential sorting

	Local Neighborhood Gini (LNG)					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.034	0.008	-0.006	-0.008	-0.021	-0.004
	(0.049)	(0.038)	(0.039)	(0.035)	(0.034)	(0.034)
Married	-0.091	-0.075	-0.050	-0.024	0.003	0.020
	(0.053)	(0.046)	(0.038)	(0.039)	(0.041)	(0.042)
Foreign Born	0.005	-0.036	0.020	0.047	0.046	0.032
	(0.069)	(0.067)	(0.056)	(0.052)	(0.048)	(0.042)
University	0.045	0.054	0.040	0.005	0.010	0.003
	(0.048)	(0.046)	(0.045)	(0.041)	(0.039)	(0.039)
Renter	0.026	0.015	-0.002	0.009	0.010	0.005
	(0.054)	(0.047)	(0.036)	(0.031)	(0.037)	(0.042)
Unemployed	-0.092	-0.093	-0.009	0.007	-0.002	0.020
	(0.067)	(0.060)	(0.052)	(0.052)	(0.051)	(0.051)
Religious	0.004	0.026	0.026	0.044	0.040	0.032
	(0.040)	(0.043)	(0.042)	(0.048)	(0.052)	(0.050)
Left-wing	-0.003	-0.079	-0.088	-0.111	-0.133	-0.108
	(0.043)	(0.046)	(0.040)	(0.042)	(0.049)	(0.045)
Age	0.040	0.041	0.034	0.017	-0.004	-0.015
	(0.023)	(0.025)	(0.025)	(0.023)	(0.021)	(0.020)
HH Size	0.021	0.029	0.028	0.018	0.018	0.016
	(0.025)	(0.022)	(0.018)	(0.018)	(0.016)	(0.015)
log HH Income	0.021	0.012	0.011	0.008	0.003	0.009
	(0.022)	(0.019)	(0.017)	(0.017)	(0.014)	(0.013)
r (meters)	100	200	350	500	750	1000
Dep Var Mean (Non-std)	0.143	0.158	0.170	0.179	0.191	0.201
Dep Var SD (Non-std)	0.050	0.045	0.045	0.046	0.047	0.046
R2	0.408	0.491	0.563	0.576	0.600	0.632
N	1330	1330	1330	1330	1330	1330
District FE	X	X	X	X	X	X

Notes: This table shows the relationship between local inequality and the observable characteristics of the individuals in the sample. All continuous variables are standardized. Local inequality is measured using the Local Neighborhood Gini (LNG), which captures inequality in dwelling values in narrowly defined neighborhoods constructed as described in Section 2.3. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. The observable characteristics considered include age, household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing Ideology, rental status, and employment status. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B4: Covariate balance across treatment and control samples

	Treated	Control	Difference
Panel A. Individual Characteristics			
Female	0.441	0.448	-0.007
	(0.022)	(0.024)	
Age	49.321	49.864	-0.544
	(0.597)	(0.683)	
Married	0.525	0.545	-0.020
	(0.022)	(0.025)	
Foreign Born	0.071	0.099	-0.029
	(0.011)	(0.015)	
University	0.601	0.550	0.052
	(0.021)	(0.025)	
Renter	0.323	0.320	0.003
	(0.020)	(0.023)	
Unemployed	0.092	0.092	-0.000
	(0.013)	(0.014)	
HH Income (1000s EUR)	47.490	45.588	1.902
	(1.560)	(2.149)	
HH Size	2.721	2.772	-0.051
	(0.052)	(0.054)	
Religious	0.313	0.339	-0.026
	(0.020)	(0.023)	
Left-wing	0.710	0.668	0.042
	(0.020)	(0.023)	
Panel B. Neighborhood Characteristics (2015)			
LNG	0.196	0.198	-0.002
	(0.002)	(0.002)	
Share Foreign	0.206	0.237	-0.031
	(0.004)	(0.006)	
Left-wing Vote Share	0.564	0.559	0.005
	(0.005)	(0.006)	
Population Density	0.045	0.041	0.004
	(0.001)	(0.001)	
Median Apartment Size	82.123	86.808	-4.684
	(0.828)	(1.325)	
Median Apartment Quality	6.084	6.063	0.021
	(0.038)	(0.058)	
Median Construction Year	1951.523	1951.245	0.278
	(0.951)	(1.330)	
N	524	413	

Notes: This table shows the covariate balance across treatment and control groups. An individual is considered treated if a new building was constructed within 350 meters from his or her dwelling in the years 2017-19. The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual covariates include age, household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing Ideology, rental status, and employment status. Neighborhood covariates (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). Standard errors in parentheses.

Table B5: New building treatment and perceived inequality (alternative identification strategies)

	Perceived Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline identification						
New Building Treatment	0.153	0.134	0.212	0.185	0.271	0.273
	(0.095)	(0.096)	(0.073)	(0.075)	(0.069)	(0.062)
Dep Var Mean (Non-std)	0.441	0.441	0.441	0.441	0.441	0.441
Dep Var SD (Non-std)	0.176	0.176	0.176	0.176	0.176	0.176
R2	0.011	0.066	0.017	0.070	0.020	0.075
N	937	937	937	937	937	937
Panel B. Ring identification						
New Building Treatment	0.068	0.043	0.128	0.109	0.214	0.251
	(0.101)	(0.101)	(0.079)	(0.082)	(0.064)	(0.061)
Dep Var Mean (Non-std)	0.453	0.453	0.449	0.449	0.445	0.445
Dep Var SD (Non-std)	0.179	0.179	0.178	0.178	0.176	0.176
R2	0.014	0.083	0.011	0.066	0.013	0.069
N	690	690	811	811	889	889
Panel C. Double ring identification						
New Building Treatment	0.312	0.285	0.412	0.367	0.519	0.421
	(0.106)	(0.106)	(0.094)	(0.081)	(0.178)	(0.186)
Inner Ring (meters)	200	200	350	350	500	500
Outer Ring (meters)	500	500	750	750	1000	1000
Dep Var Mean (Non-std)	0.433	0.433	0.443	0.443	0.446	0.446
Dep Var SD (Non-std)	0.174	0.174	0.177	0.177	0.179	0.179
R2	0.037	0.112	0.034	0.101	0.026	0.089
N	522	522	650	650	738	738
Indiv Controls		X		X		X
N'hood Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table tests the robustness of the baseline results from Table 5 (top panel) on perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built in 2017-19). Sample is restricted to individuals residing in the same dwelling from at least 2015. Panel A replicates the results using the baseline identification strategy. Panel B restricts the control group to only include individuals residing within 500, 750, or 1000 meters from a new construction. Panel C restricts the control sample to only include individuals residing farther than 500, 750, or 1000 meters from a new construction. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B6: New building treatment and preferences for redistribution (alternative identification strategies)

	Preferences for Redistribution					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline identification						
New Building Treatment	0.078	0.018	0.112	0.034	0.127	0.036
	(0.070)	(0.063)	(0.058)	(0.057)	(0.068)	(0.056)
Dep Var Mean (Non-std)	6.487	6.487	6.487	6.487	6.487	6.487
Dep Var SD (Non-std)	2.311	2.311	2.311	2.311	2.311	2.311
R2	0.010	0.176	0.012	0.176	0.012	0.176
N	937	937	937	937	937	937
Panel B. Ring identification						
New Building Treatment	0.050	0.021	0.076	0.023	0.089	-0.005
	(0.080)	(0.070)	(0.068)	(0.066)	(0.079)	(0.070)
Dep Var Mean (Non-std)	6.559	6.559	6.534	6.534	6.523	6.523
Dep Var SD (Non-std)	2.335	2.335	2.307	2.307	2.293	2.293
R2	0.006	0.176	0.011	0.176	0.013	0.186
N	690	690	811	811	889	889
Panel C. Double ring identification						
New Building Treatment	0.101	0.056	0.190	0.059	0.309	0.132
	(0.083)	(0.079)	(0.084)	(0.089)	(0.195)	(0.214)
Inner Ring (meters)	200	200	350	350	500	500
Outer Ring (meters)	500	500	750	750	1000	1000
Dep Var Mean (Non-std)	6.467	6.467	6.514	6.514	6.511	6.511
Dep Var SD (Non-std)	2.282	2.282	2.337	2.337	2.355	2.355
R2	0.023	0.177	0.012	0.170	0.010	0.170
N	522	522	650	650	738	738
Indiv Controls		X		X		X
N'hood Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table tests the robustness of the baseline results from Table 5 (bottom panel) on preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built in 2017-19). Sample is restricted to individuals residing in the same dwelling from at least 2015. Panel A replicates the results using the baseline identification strategy. Panel B restricts the control group to only include individuals residing within 500, 750, or 1000 meters from a new construction. Panel C restricts the control sample to only include individuals residing farther than 500, 750, or 1000 meters from a new construction. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B7: New building treatment and perceived inequality (alternative time windows)

	Perceived Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Three-year window (baseline)						
New Building Treatment in 2017-19	0.134 (0.096)	0.134 (0.096)	0.185 (0.075)	0.185 (0.075)	0.273 (0.062)	0.273 (0.062)
Dep Var Mean (Non-std)	0.441	0.441	0.441	0.441	0.441	0.441
Dep Var SD (Non-std)	0.176	0.176	0.176	0.176	0.176	0.176
R2	0.066	0.066	0.070	0.070	0.075	0.075
N	937	937	937	937	937	937
Panel B. Two-year window						
New Building Treatment in 2018-19	0.091 (0.096)	0.106 (0.104)	0.086 (0.074)	0.160 (0.081)	0.149 (0.076)	0.280 (0.073)
Dep Var Mean (Non-std)	0.438	0.438	0.436	0.436	0.437	0.437
Dep Var SD (Non-std)	0.173	0.173	0.171	0.171	0.173	0.173
R2	0.064	0.061	0.064	0.062	0.067	0.081
N	937	863	937	827	937	849
Panel C. One-year window						
New Building Treatment in 2019	-0.023 (0.140)	0.037 (0.142)	0.012 (0.086)	0.148 (0.101)	0.118 (0.077)	0.261 (0.092)
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	0.435	0.435	0.431	0.431	0.434	0.434
Dep Var SD (Non-std)	0.172	0.172	0.169	0.169	0.169	0.169
R2	0.063	0.058	0.063	0.060	0.065	0.083
N	937	779	937	675	937	666
Indiv Controls	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X
District FE	X	X	X	X	X	X
No Previous Exposure		X		X		X

Notes: This table tests the robustness of the baseline results from Table 5 (top panel) on perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built within the past one (Panel C), two (Panel B) or three (Panel A) years). Sample is restricted to individuals residing in the same dwelling from at least 2015. *No Previous Exposure* (Columns 2, 4, and 6) further restricts the sample to individuals not having been exposed to a new building treatment before the time window considered. This implies excluding individuals exposed to treatment in 2017 (Panel B) or 2017 and 2018 (Panel C). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B8: New building treatment and preferences for redistribution (alternative time windows)

	Preferences for Redistribution					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Three-year window (baseline)						
New Building Treatment in 2017-19	0.018	0.018	0.034	0.034	0.036	0.036
	(0.063)	(0.063)	(0.057)	(0.057)	(0.056)	(0.056)
Dep Var Mean (Non-std)	6.487	6.487	6.487	6.487	6.487	6.487
Dep Var SD (Non-std)	2.311	2.311	2.311	2.311	2.311	2.311
R2	0.176	0.176	0.176	0.176	0.176	0.176
N	937	937	937	937	937	937
Panel B. Two-year window						
New Building Treatment in 2018-19	0.041	0.028	0.063	0.051	0.028	0.039
	(0.077)	(0.075)	(0.065)	(0.060)	(0.057)	(0.060)
Dep Var Mean (Non-std)	6.494	6.494	6.520	6.520	6.496	6.496
Dep Var SD (Non-std)	2.318	2.318	2.299	2.299	2.333	2.333
R2	0.176	0.179	0.177	0.180	0.176	0.176
N	937	863	937	827	937	849
Panel C. One-year window						
New Building Treatment in 2019	0.005	0.022	0.044	0.063	0.103	0.108
	(0.105)	(0.101)	(0.068)	(0.070)	(0.059)	(0.070)
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	6.462	6.462	6.489	6.489	6.512	6.512
Dep Var SD (Non-std)	2.306	2.306	2.286	2.286	2.310	2.310
R2	0.176	0.182	0.176	0.177	0.178	0.183
N	937	779	937	675	937	666
Indiv Controls	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X
District FE	X	X	X	X	X	X
No Previous Exposure		X		X		X

Notes: This table tests the robustness of the baseline results from Table 5 (bottom panel) on demand for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new construction (built within the past one (Panel C), two (Panel B), or three (Panel A) years). Sample is restricted to individuals residing in the same dwelling from at least 2015. *No Previous Exposure* (Columns 2, 4, and 6) further restricts the sample to individuals not having been exposed to a new building treatment before the time window considered. This implies excluding individuals exposed to treatment in 2017 (Panel B) or 2017 and 2018 (Panel C). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B9: Local inequality (LNG) and perceived inequality — IV Results

	Perceived Gini							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ LNG (Value)	-0.024	-0.001	6.639	4.712				
	(0.046)	(0.045)	(32.504)	(15.627)				
Δ LNG (Space)					0.079	0.076	0.568	0.448
					(0.038)	(0.033)	(0.241)	(0.211)
Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Dep Var Mean (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
Kleibergen-Paap LM			0.041	0.089			11.345	10.696
R2	0.007	0.063			0.012	0.068		
N	937	937	937	937	937	937	937	937
Indiv Controls		X		X		X		X
N'hood Controls		X		X		X		X
District FE	X	X	X	X	X	X	X	X

Notes: This table shows the effects of a change in local inequality on perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. ΔLNG ($r = 350$) measures the percentage change in LNG during 2016-19 in either dwelling value or space. These variables are instrumented using *New Building Treatment*, an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B10: Local inequality (LNG) and preferences for redistribution — IV Results

	Preferences for Redistribution							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ LNG (Value)	-0.043	-0.052	3.519	0.855				
	(0.034)	(0.029)	(17.531)	(3.443)				
Δ LNG (Space)					0.042	0.050	0.301	0.081
					(0.029)	(0.025)	(0.177)	(0.138)
Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339
Kleibergen-Paap LM			0.041	0.089			11.345	10.696
R2	0.010	0.178			0.011	0.178		
N	937	937	937	937	937	937	937	937
Indiv Controls		X		X		X		X
N'hood Controls		X		X		X		X
District FE	X	X	X	X	X	X	X	X

Notes: This table shows the effects of a change in local inequality on preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. ΔLNG ($r = 350$) measures the percentage change in LNG during 2016-19 in either dwelling value or space. These variables are instrumented using *New Building Treatment*, an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B11: New apartment building treatment and inequality perceptions (alternative measures)

	log Perceived 90/10 Income Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
New Building Treatment	0.233	0.219	0.205	0.193	0.211	0.211
	(0.091)	(0.095)	(0.065)	(0.067)	(0.065)	(0.063)
Dep Var Mean (Non-std)	2.241	2.241	2.241	2.241	2.241	2.241
Dep Var SD (Non-std)	1.391	1.391	1.391	1.391	1.391	1.391
R2	0.019	0.042	0.018	0.041	0.016	0.040
N	937	937	937	937	937	937
	log Perceived 90/50 Income Ratio					
New Building Treatment	0.191	0.165	0.195	0.161	0.241	0.230
	(0.095)	(0.097)	(0.072)	(0.075)	(0.072)	(0.067)
Dep Var Mean (Non-std)	1.121	1.121	1.121	1.121	1.121	1.121
Dep Var SD (Non-std)	0.780	0.780	0.780	0.780	0.780	0.780
R2	0.011	0.047	0.012	0.048	0.014	0.051
N	937	937	937	937	937	937
	Perceived Gini (Pyramid)					
New Building Treatment	0.110	0.104	0.018	0.005	0.047	0.010
	(0.073)	(0.069)	(0.060)	(0.057)	(0.083)	(0.078)
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	0.327	0.327	0.327	0.327	0.327	0.327
Dep Var SD (Non-std)	0.075	0.075	0.075	0.075	0.075	0.075
R2	0.024	0.083	0.022	0.081	0.022	0.081
N	937	937	937	937	937	937
Indiv Controls		X		X		X
N'hood Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table tests the robustness of the baseline results from Table 5 (top panel) on perceived inequality, in this instance using alternatives to *Perceived Gini*. All continuous variables are standardized. *log Perceived 90/10 Income Ratio* and *log Perceived 90/50 Income Ratio* denote the logarithm of the income ratios based on the percentiles 90, 50, or 10 of respondents' perceived income distribution. *Perceived Gini (Pyramid)* is the inferred Gini coefficient based on the ISSP pyramid question (see Figure B3), following the methodology in Gimpelson and Treisman (2018). *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 200 (Columns 1-2), 350 (Columns 3-4), or 500 (Columns 5-6) meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B12: New building treatment and preferences for redistribution (alternative measures)

	(1)	(2)	(3)	(4)	(5)	(6)
	Preferences for Redistribution (No Trade-off)					
New Building Treatment	0.121	0.102	0.031	0.005	0.136	0.114
	(0.061)	(0.063)	(0.064)	(0.064)	(0.072)	(0.072)
Dep Var Mean (Non-std)	5.994	5.994	5.994	5.994	5.994	5.994
Dep Var SD (Non-std)	2.552	2.552	2.552	2.552	2.552	2.552
R2	0.016	0.094	0.014	0.092	0.017	0.094
N	937	937	937	937	937	937
	Voted a Left-wing Party					
New Building Treatment	0.042	0.013	0.063	0.030	0.062	0.038
	(0.032)	(0.031)	(0.034)	(0.030)	(0.033)	(0.030)
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	0.725	0.725	0.725	0.725	0.725	0.725
Dep Var SD (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447
R2	0.039	0.365	0.041	0.366	0.040	0.366
N	828	828	828	828	828	828
Indiv Controls		X		X		X
N'hood Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table investigates the effects of the new building treatment on demand for redistribution. All continuous variables are standardized. *Preferences for Redistribution (No Trade-off)* measures demand for redistribution in a scale from 0 to 10 using a question borrowed from Fehr et al. (2019). *Voted a Left-wing Party* is an indicator taking the value of 1 if the individual voted for a left-wing party in the November 2019 national election. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 200 (Columns 1-2), 350 (Columns 3-4), or 500 (Columns 5-6) meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table B13: New building treatment and votes for the left-wing parties (aggregate electoral data)

	Left-wing Parties Vote Share					
New Building Treatment	0.162 (0.065)	0.037 (0.021)	0.250 (0.086)	0.074 (0.025)	0.292 (0.093)	0.080 (0.033)
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	0.639	0.639	0.639	0.639	0.639	0.639
Dep Var SD (Non-std)	0.091	0.091	0.091	0.091	0.091	0.091
R2	0.637	0.908	0.644	0.909	0.645	0.909
N	1058	1058	1058	1058	1058	1058
Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table investigates the effects of the new building treatment on demand for redistribution using aggregate electoral data. All continuous variables are standardized. *Left-wing Parties Parties Vote Share* is the (census tract) vote share obtained by left-wing parties in the November 2019 national election. *New Building Treatment* is an indicator taking the value of 1 if the census tract's centroid is located within 200 (Columns 1-2), 350 (Columns 3-4), or 500 (Columns 5-6) meters of a new apartment building constructed in 2017-19. Controls (at the census tract level) include mean age, log median household income (2017), share Female, share foreign-born, share of university graduates (2011), share married (2011), left-wing parties vote share in the 2015 national election, share of rentals, share of households with unemployment insurance or other subsidies as main source of income (2017). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

C Heterogeneity

C.1 Overview

I study heterogeneity in inequality perceptions, preferences for redistribution, and treatment effects. The dimensions explored are ideology, education, rental status, income (above and below 1,144 EUR per month according to the *Encuesta de Condiciones de Vida*), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender. Results point at ideology, education, income, and country of origin as the most relevant dimensions of heterogeneity.

C.2 Perceived inequality and preferences for redistribution

I start by investigating the accuracy of perceived income distributions in Figure C1. In that and the following figures, I split the sample along a binary variable and show the same results separately for each subsample.

All individual subsamples do a decent job at guessing the actual incomes across percentiles, but there are noticeable differences along some dimensions. As in Figure B1, respondents do especially well in predicting the incomes at the lower percentiles, but they generally overestimate incomes at the top. Perhaps surprisingly, individuals without a college degree and below the median national income (1,144 EUR per month) generally do better predicting incomes in the top percentiles as they tend to introduce lower amounts. In fact, in contrast with most of the sample splits, low-income individuals slightly underestimate income at all percentiles, whereas high-income individuals slightly overestimate incomes throughout the distribution. Another relevant dimension is ideology. Relative to right-wing individuals, left-wingers perceive lower incomes at the bottom and higher at the top.

Figure C2 shows the cumulative distributions of *Perceived Gini* along the same dimensions and sample splits. Consistent with previous results, individuals with a college degree and, especially, left-wingers perceive more inequality. The CDF for this latter group first-order stochastically dominates that of right-wingers, a result in line with Chambers et al. (2014). Apart from these two categories, non-religious individuals also perceive slightly more inequality. Visually, there are no significant differences across the rest of the sample splits.

Figure C3 shows the cumulative distributions of *Preferences for Redistribution* along the same dimensions and sample splits. Ideology is again the most relevant split. Relative to right-wing individuals, left-wingers are significantly more in favor of redistribution, as suggested by the first-order stochastic dominance of the distribution. Non-religious individuals, renters, and college graduates also appear to be more in favor of redistribution generally. Nonetheless, the contrast is not as stark.

C.3 New apartment building treatment

Tables C1 and C2 explore the heterogeneous effects of the new apartment building treatment. Effects are particularly strong among left-wingers, that significantly perceive more inequality after being treated. However, this subgroup's effect on demand for redistribution is not statistically different from zero. Similar patterns arise among the low-educated, low-income, young, singles, and natives. Within these groups, treatment effects range between 20 and 30% of a SD (3.5 to 5.3 points in *Perceived Gini*). As with ideology, the differences in demand for redistribution are not significant.

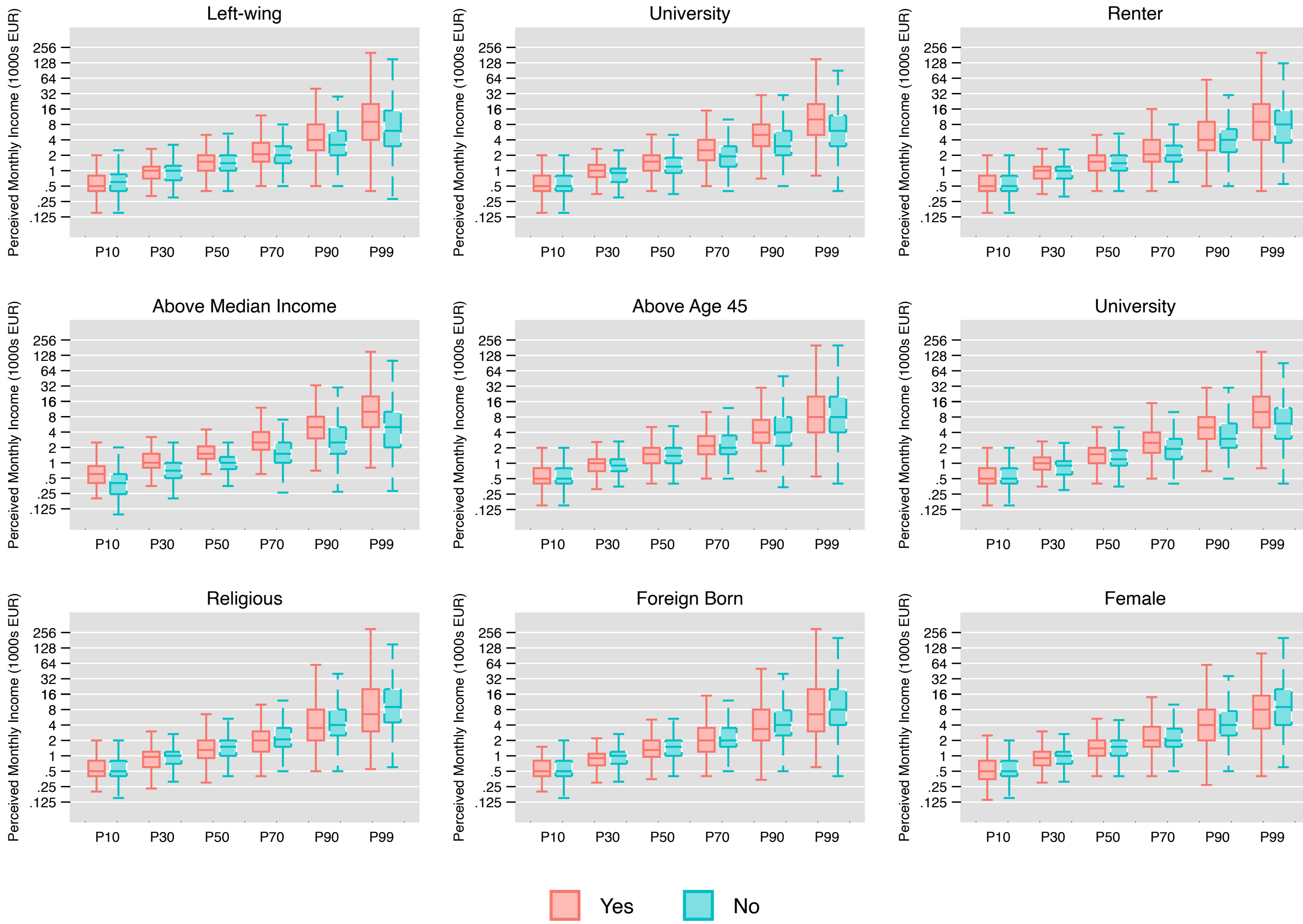


Figure C1: Perceived income distributions among respondents (heterogeneity)

Notes: This figure explores heterogeneity in the perceived national income distribution among survey respondents along several dimensions. The heterogeneity dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male). The figure excludes outliers. The y-axis is log-scaled. The median perceived monthly incomes for the percentiles 10, 30, 50, 70, 90, and 99 were 500, 1000, 1400, 2000, 4000, and 8000, respectively. According to the *Encuesta de Condiciones de Vida* (INE, 2018), the actual monthly incomes in these percentiles in the year 2018 were 446, 790, 1144, 1678, 2795, and 5791, respectively.

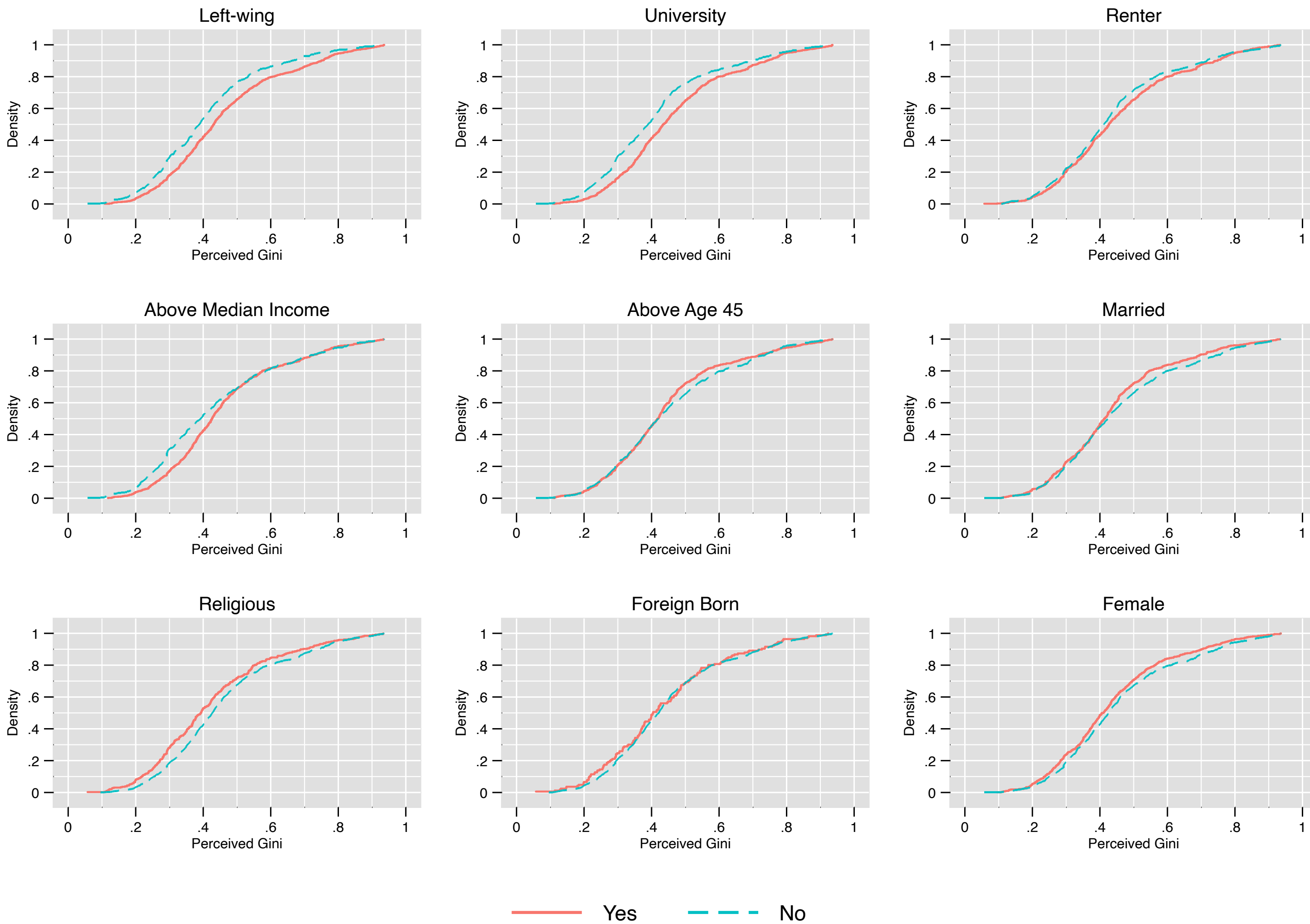


Figure C2: Cumulative distributions of *Perceived Gini* (heterogeneity)

Notes: This figure shows heterogeneity in the Cumulative Distribution Functions (CDF) of *Perceived Gini* along several dimensions. *Perceived Gini* is the Gini index of the respondent's perceived national income distribution. Each figure plots the separate CDFs resulting from splitting the sample along a binary covariate. The dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male).

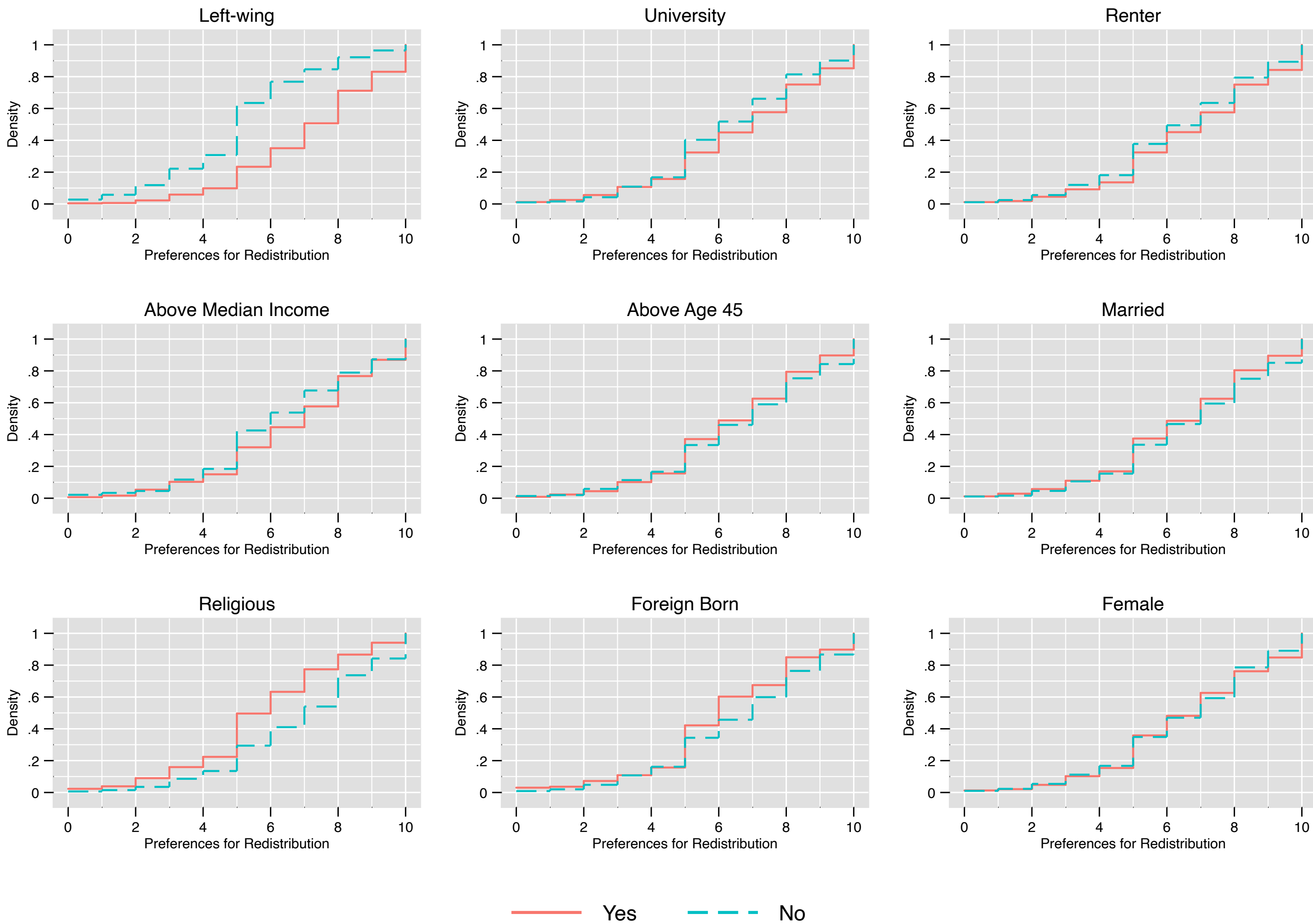


Figure C3: Cumulative distributions of *Preferences for Redistribution* (heterogeneity)

Notes: This figure shows heterogeneity in the Cumulative Distribution Functions (CDF) of *Preferences for Redistribution* along several dimensions. *Preferences for Redistribution* measures demand for redistribution on a scale from 0 to 10, with 10 representing the highest demand for redistribution. Each figure plots the separate CDFs resulting from splitting the sample along a binary covariate. The dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male).

Table C1: New apartment building treatment and perceived inequality (heterogeneity)

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.185 (0.075)	-0.013 (0.125)	0.125 (0.116)	0.179 (0.086)	0.208 (0.120)	0.382 (0.119)	0.323 (0.101)	0.184 (0.072)	0.224 (0.079)	0.151 (0.112)
New Building Treatment × Left-wing		0.295 (0.133)								
New Building Treatment × University			0.109 (0.148)							
New Building Treatment × Renter				0.026 (0.128)						
New Building Treatment × Above Med Inc					-0.031 (0.133)					
New Building Treatment × Above Age 45						-0.295 (0.138)				
New Building Treatment × Married							-0.249 (0.119)			
New Building Treatment × Religious								0.010 (0.127)		
New Building Treatment × Foreign Born									-0.429 (0.243)	
New Building Treatment × Female										0.085 (0.138)
Sum of Treatment Effects	0.185 (0.075)	0.282 (0.083)	0.234 (0.100)	0.205 (0.120)	0.177 (0.088)	0.088 (0.091)	0.074 (0.096)	0.194 (0.137)	-0.205 (0.237)	0.236 (0.092)
Dep Var Mean (Non-std)	0.441	0.441	0.441	0.441	0.441	0.441	0.441	0.441	0.441	0.441
Dep Var SD (Non-std)	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
R2	0	0	0	0	0	0	0	0	0	0
N	937	937	937	937	937	937	937	937	937	937
Indiv Controls	X	X	X	X	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X

Notes: This table explores heterogeneity in the effects of the new apartment building treatment on perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who already resided in the same dwelling in 2015. The heterogeneity dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table C2: New apartment building treatment and preferences for redistribution (heterogeneity)

	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.034 (0.057)	0.013 (0.106)	0.092 (0.085)	0.024 (0.075)	0.019 (0.089)	0.045 (0.107)	-0.006 (0.085)	-0.021 (0.076)	0.044 (0.059)	0.040 (0.076)
New Building Treatment × Left-wing		0.034 (0.136)								
New Building Treatment × University			-0.098 (0.122)							
New Building Treatment × Renter				0.038 (0.131)						
New Building Treatment × Above Med Inc					0.025 (0.119)					
New Building Treatment × Above Age 45						-0.014 (0.144)				
New Building Treatment × Married							0.076 (0.115)			
New Building Treatment × Religious								0.173 (0.142)		
New Building Treatment × Foreign Born									-0.102 (0.190)	
New Building Treatment × Female										-0.011 (0.113)
Sum of Treatment Effects	0.034 (0.057)	0.047 (0.073)	-0.006 (0.079)	0.062 (0.098)	0.044 (0.074)	0.031 (0.076)	0.070 (0.076)	0.152 (0.106)	-0.057 (0.181)	0.030 (0.083)
Dep Var Mean (Non-std)	6.487	6.487	6.487	6.487	6.487	6.487	6.487	6.487	6.487	6.487
Dep Var SD (Non-std)	2.311	2.311	2.311	2.311	2.311	2.311	2.311	2.311	2.311	2.311
R2	0	0	0	0	0	0	0	0	0	0
N	937	937	937	937	937	937	937	937	937	937
Indiv Controls	X	X	X	X	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X

Notes: This table explores heterogeneity in the effects of the new apartment building treatment on demand for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). The sample is restricted to individuals who already resided in the same dwelling in 2015. The heterogeneity dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

D Information experiment

D.1 Identification and empirical strategy

The survey contained an experiment to induce variation in the information set about local inequality *between* neighborhoods. Respondents had a 50% chance of being exposed to the question shown in Figure D1. The question contains a simple table showing the average price of a dwelling across Barcelona's ten districts. Treated individuals saw the table and had to respond to two simple attention-check questions.[7] I excluded individuals that failed to answer both questions correctly for this part of the analysis.[8] I estimate the average effects of the treatment with the following model:

$$Y_i = \beta Treated_i + X_i^{'}\gamma + \epsilon_i \tag{3}$$

where Y_i is an outcome variable of interest (e.g., *Perceived Gini*) measured for individual i. $Treated_i$ is an indicator variable taking the value of 1 if the individual was exposed to the information treatment during the survey. X_i is the same vector of controls as in Section 5. The model does not include fixed effects as the treatment does not generate variation within districts (i.e., all individuals in the same district see the same table). β captures the average treatment effect.

Covariate balance: Table D1 shows that the sample is well balanced. None of the covariates used as controls is statistically different across subsamples.

D.2 Information treatment, perceived inequality, and preferences for redistribution

Perceived inequality: Columns 1 and 2 in Table D2 study the effects of the information treatment on perceived inequality. Results suggest that exposure to the treatment increases *Perceived Gini* by approximately 7% of a SD (translating into 1.1 points, or 2.5% of the mean). The effects are small and statistically indistinguishable from zero. The coefficients are not significantly different when including controls.

Preferences for redistribution: Columns 3 and 4 in the same table look at preferences for redistribution. The treatment increases demand for redistribution by approximately 7% of a SD (0.16 points, or about 2.5% of the mean). Effects are not statistically significant.

Results in Table D2 show a small effect of the treatment on both outcomes. At least two mechanisms could explain the present results. A first possibility is that the treatment is weak, perhaps "too informational'.'[9] A second hypothesis is that information about more distant neighborhoods is not as relevant. Next, I try to disentangle both stories by digging deeper into the effects of the treatment and looking at heterogeneity.

D.3 Mechanisms and heterogeneity

Perceived income distribution: The treatment right-shifted the entire perceived income distribution, but slightly more in the right tail. Table D3 shows positive shifts across all percentiles ranging from six to 12%

[7]The questions asked them the location of the most and least expensive dwellings in the city.

[8]Also those that spent less than 20 seconds on the treatment page (5th percentile of the time distribution).

[9]Information treatments are sometimes unable to shift beliefs. Research suggests that these types of experiments are more effective when they are less informational and have a strong visual or emotional component (Engelhardt and Wagener 2018, Kuziemko et al. 2015).

of a SD (1.3 to 2.5% of the mean). These shifts are slightly larger and more significant at the top (percentiles 90 and 99) and in the middle (percentiles 50 and 30). In other words, the treatment did not significantly affect beliefs about inequality but made participants think there was more income to redistribute. That explains the positive but not significant effect on *Perceived Gini*, and it might partly explain the small effect on *Preferences for Redistribution* documented in Table D2.

District of residence: In addition to information about local inequality, the treatment also conveys some information about respondents' relative position in the city. It reminds participants whether they reside in an affluent or less-affluent neighborhood. Prior research suggests that individuals care about their relative position within a distribution (Cruces et al. 2013, Luttmer 2005, Perez-Truglia 2020). Thus, I next look at whether treatment effects differ depending on respondents' district of residence, in Table D4. There, $PoorDistrict$ is an indicator taking the value of 1 if the individual resides in one of the five poorest districts in the city according to the information given in the treatment.[10]

Columns 1-2 and 5-6 replicate Table D2 and add the *Poor District* indicator. Average treatment effects remain at approximately 7% of a SD for both outcomes after the inclusion of this new variable. The negative and marginally significant coefficient on *Poor District* (Columns 1-2) is possibly unexpected, but it is consistent with local and perceived inequality being positively associated. In Barcelona, poorer districts are, on average, less unequal. For example, the average LNG ($r = 200$) associated with individuals' dwellings in the less affluent districts is 0.135 (SD of 0.030), whereas the respective figure in the wealthier districts is 0.190 (0.043).[11] Columns 3-4 show no significant differences across both groups of districts in terms of demand for redistribution on average. The effect is, on average, positive but negative and close to significant when looking at untreated individuals in poorer districts (Columns 7-8).[12]

Treatment effects on demand for redistribution significantly differ across districts. Columns 3-4 and 7-8 re-estimate Equation 3 and include an interaction with *Poor District*. Columns 7-8 show that while treated individuals in the wealthier districts respond by demanding *less* redistribution (-7% of a SD, not significant), those in the poorer districts react by demanding more (about 18% of a SD, 0.4 points or 6% of the mean). A shift in perceived inequality cannot explain this increase in demand for redistribution. *Perceived Gini* increases by approximately 5% of a SD (0.9 points) in the wealthier districts and by 8% of a SD (1.4 points) in the least affluent ones. These are small effects and not statistically distinguishable from zero. Instead, a more plausible explanation is a combination of the observed right-shift in perceived income — slightly larger in the less affluent districts (Table D5) — coupled with the treatment making respondents' relative position within the city more salient. The latter effect might have induced participants to realize they were poorer (or richer) than they thought, and that might have triggered the shift in demand for redistribution.[13]

Other factors: I study heterogeneity along other observables in Tables D6 and D7. Treatment effects are larger among low-income, low-educated, and natives. Treated individuals without a college degree increase their perceived inequality and demand for redistribution by almost 15% of a SD. Those with low incomes experience similar shifts. In contrast, those with a college degree or higher income see essentially no changes in either outcome. Treated individuals born in Spain experience an increase in perceived inequality and

[10]These are Nou Barris, Horta-Guinardó, Sants-Montjuïc, Sant Andreu, and Sant Martí.

[11]The same figures in the population are 0.136 (0.032) and 0.185 (0.043) for the poorer and wealthier districts, respectively. They are virtually identical to those in the sample, thus highlighting the sample's good representativity in terms of geography.

[12]Untreated individuals in those districts also perceive less inequality (Columns 3-4).

[13]A result consistent with previous research (e.g., Cruces et al. 2013, Sands 2017).

demand for redistribution between 6 and 9% of a SD. Effects are also slightly stronger among left-wingers and older individuals, but differences are not significant.

One story consistent with the previous results is that some groups (low-income, low-educated, and natives) see their local neighborhood and city as relatively more important reference points and thus react more to the treatment. This story is consistent with recent research in the US context (Minkoff and Lyons 2019, Newman et al. 2015).[14]

D.4 Discussion

Relative to the new building treatment, the information experiment is less effective in shifting perceived inequality or demand for redistribution. A first rationalization was that the experimental design was "too clinical" to shift perceptions (Kuziemko et al. 2015) effectively. However, I documented a clear shift in the perceived income distribution of respondents (Table D3) and significant heterogeneities based on, for instance, respondents' district of residence (Table D4). These are inconsistent with the treatment being too weak. A second explanation is that knowledge about more distant places does not shape perceptions or demand for redistribution *as much*. A fundamental difference between the two approaches to identification is the aggregation level at which variation is generated. While the new apartment building treatment exploits variation *within* neighborhoods (close to respondents' dwellings), the information treatment generates variation *across* neighborhoods (by giving information about places "far" from respondents' homes). Therefore, an interpretation for the differences in the results is that, effectively, what is close is more relevant.

[14]In fact, similar heterogeneities arise when looking at the new apartment building treatment (Tables C1 and C2).

The following table shows the average price of a dwelling* in each of the 10 districts of Barcelona

District	€
Ciutat Vella	322.275
Eixample	455.221
Sants-Montjuïc	280.608
Les Corts	537.948
Sarrià-Sant Gervasi	706.180
Gràcia	355.725
Horta-Guinardó	256.400
Nou Barris	188.774
Sant Andreu	263.548
Sant Martí	317.942

Source: Catastro, Idealista, Ajuntament de Barcelona

* Used dwelling

Which district has, on average, the most expensive dwellings?

Which district has, on average, the cheapest dwellings?

Figure D1: Screenshot of the survey information treatment

Notes: This figure shows a screenshot of the (translated) information treatment in the survey. 50% of the respondents were randomly exposed to the table above, showing the average prices of a dwelling in Barcelona's ten districts. As an attention check, participants had to answer two simple questions about the table. The treatment gives respondents some information about local inequality in the city. It also conveys information about the respondents' relative position within the city. Prices in the table are calculated using information from the Cadastre, the Barcelona City Council, and Idealista (a real-estate website).

Table D1: Covariate balance across treatment and control samples (information treatment)

	Treated	Control	Difference
Panel A. Individual Characteristics			
Female	0.468	0.464	0.004
	(0.021)	(0.020)	
Age	45.792	45.734	0.058
	(0.592)	(0.565)	
Married	0.464	0.421	0.043
	(0.021)	(0.019)	
Foreign Born	0.109	0.144	-0.035
	(0.013)	(0.014)	
University	0.633	0.641	-0.007
	(0.020)	(0.019)	
Renter	0.444	0.447	-0.003
	(0.021)	(0.020)	
Unemployed	0.099	0.109	-0.010
	(0.012)	(0.012)	
HH Income (1000s EUR)	46.519	46.213	0.306
	(1.652)	(1.474)	
HH Size	2.672	2.637	0.035
	(0.046)	(0.046)	
Religious	0.283	0.303	-0.019
	(0.019)	(0.018)	
Left-wing	0.700	0.714	-0.015
	(0.019)	(0.018)	
Panel B. Neighborhood Characteristics (2015)			
LNG	0.200	0.197	0.002
	(0.002)	(0.002)	
Share Foreign	0.227	0.222	0.005
	(0.005)	(0.004)	
Left-wing Vote Share	0.556	0.563	-0.007
	(0.005)	(0.005)	
Population Density	0.044	0.043	0.000
	(0.001)	(0.001)	
Median Apartment Size	84.431	83.568	0.863
	(0.929)	(0.888)	
Median Apartment Quality	6.070	6.072	-0.002
	(0.043)	(0.039)	
Median Construction Year	1950.616	1949.263	1.353
	(1.015)	(0.972)	
N	586	651	

Notes: This table shows the covariate balance across treatment and control groups for the information experiment. Individual covariates include age, household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing Ideology, rental status, and employment status. Neighborhood covariates (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. Standard errors in parentheses.

Table D2: Information treatment, perceived inequality, and preferences for redistribution

	Perceived Gini		Pref Redistribution	
	(1)	(2)	(3)	(4)
N'hood Info Treatment	0.064	0.060	0.064	0.074
	(0.052)	(0.051)	(0.046)	(0.046)
Dep Var Mean (Non-std)	0.452	0.452	6.601	6.601
Dep Var SD (Non-std)	0.178	0.178	2.302	2.302
R2	0.001	0.017	0.001	0.028
N	1237	1237	1237	1237
Indiv Controls		X		X
N'hood Controls		X		X

Notes: This table shows the effects of the neighborhood information treatment on perceived inequality and preferences for redistribution. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table D3: Neighborhood information treatment and perceived income

	Perceived P99		Perceived P90		Perceived P70		Perceived P50		Perceived P30		Perceived P10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
N'hood Info Treatment	0.121	0.109	0.107	0.092	0.080	0.062	0.101	0.083	0.124	0.106	0.070	0.057
	(0.055)	(0.053)	(0.055)	(0.049)	(0.052)	(0.046)	(0.055)	(0.048)	(0.053)	(0.047)	(0.045)	(0.043)
Dep Var Mean (Non-std)	9.252	9.252	8.423	8.423	7.743	7.743	7.255	7.255	6.813	6.813	6.128	6.128
Dep Var SD (Non-std)	1.848	1.848	1.401	1.401	1.154	1.154	1.048	1.048	1.037	1.037	1.331	1.331
R2	0.004	0.060	0.003	0.068	0.002	0.080	0.003	0.088	0.004	0.096	0.001	0.089
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
Indiv Controls		X		X		X		X		X		X
N'hood Controls		X		X		X		X		X		X

Notes: This table shows the effects of the neighborhood information treatment on perceived income. All continuous variables are standardized. *Perceived P99*, *Perceived P90*, *Perceived P70*, *Perceived P50*, *Perceived P30*, and *Perceived P10* denote perceived log income at a given percentile. *Poor district* is an indicator taking the value of 1 if the respondent resides in one of the five poorest districts according to the information treatment (see Figure D1). These are Nou Barris, Horta-Guinardó, Sant Andreu, Sants-Montjuïc, and Sant Martí. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table D4: Information treatment, perceived inequality, and preferences for redistributions – Effects by district of residence

	Perceived Gini				Preferences for Redistribution			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N'hood Info Treatment	0.063	0.060	0.044	0.034	0.064	0.073	-0.060	-0.072
	(0.052)	(0.051)	(0.059)	(0.058)	(0.046)	(0.047)	(0.061)	(0.062)
Poor District	-0.111	-0.061	-0.127	-0.082	0.024	0.025	-0.081	-0.090
	(0.065)	(0.101)	(0.071)	(0.106)	(0.050)	(0.063)	(0.065)	(0.077)
N'hood Info Treatment			0.033	0.046			0.221	0.256
$\times$ Poor District			(0.099)	(0.096)			(0.085)	(0.085)
Sum of Treatment Effects			0.077	0.080			0.160	0.185
			(0.079)	(0.078)			(0.059)	(0.059)
Dep Var Mean (Non-std)	0.452	0.452	0.452	0.452	6.601	6.601	6.601	6.601
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	2.302	2.302	2.302	2.302
R2	0.004	0.017	0.004	0.017	0.001	0.028	0.004	0.032
N	1237	1237	1237	1237	1237	1237	1237	1237
Indiv Controls		X		X		X		X
N'hood Controls		X		X		X		X

Notes: This table shows the effects of the neighborhood information treatment on perceived inequality and preferences for redistribution, looking at heterogeneous effects by district of residence. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *Poor district* is an indicator taking the value of 1 if the respondent resides in one of the five poorest districts according to the information treatment (see Figure D1). These are Nou Barris, Horta-Guinardó, Sant Andreu, Sants-Montjuïc, and Sant Martí. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table D5: Neighborhood information treatment and perceived income — Effects by district of residence

	Perceived P99		Perceived P90		Perceived P70		Perceived P50		Perceived P30		Perceived P10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
N'hood Info Treatment	0.112	0.074	0.092	0.063	0.058	0.043	0.077	0.068	0.100	0.084	0.053	0.027
	(0.057)	(0.072)	(0.050)	(0.074)	(0.046)	(0.074)	(0.049)	(0.085)	(0.047)	(0.081)	(0.042)	(0.068)
Poor District	-0.060	-0.090	-0.046	-0.068	-0.100	-0.112	-0.103	-0.110	-0.097	-0.109	-0.016	-0.036
	(0.097)	(0.105)	(0.091)	(0.104)	(0.090)	(0.110)	(0.087)	(0.111)	(0.082)	(0.110)	(0.065)	(0.079)
N'hood Info Treatment		0.067		0.050		0.026		0.016		0.027		0.045
$\times$ Poor District		(0.105)		(0.102)		(0.098)		(0.105)		(0.102)		(0.091)
Sum of Treatment Effects		0.141		0.113		0.069		0.084		0.112		0.072
		(0.080)		(0.069)		(0.062)		(0.059)		(0.058)		(0.056)
Dep Var Mean (Non-std)	9.252	9.252	8.423	8.423	7.743	7.743	7.255	7.255	6.813	6.813	6.128	6.128
Dep Var SD (Non-std)	1.848	1.848	1.401	1.401	1.154	1.154	1.048	1.048	1.037	1.037	1.331	1.331
R2	0.086	0.086	0.086	0.087	0.092	0.092	0.095	0.095	0.101	0.101	0.096	0.097
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
Indiv Controls	X	X	X	X	X	X	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows the effects of the neighborhood information treatment on perceived income. All continuous variables are standardized. *Perceived P99*, *Perceived P90*, *Perceived P70*, *Perceived P50*, *Perceived P30*, and *Perceived P10* denote perceived log income at a given percentile. *Poor district* is an indicator taking the value of 1 if the respondent resides in one of the five poorest districts according to the information treatment (see Figure D1). These are Nou Barris, Horta-Guinardó, Sant Andreu, Sants-Montjuïc, and Sant Martí. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table D6: Neighborhood information treatment and perceived inequality (heterogeneity)

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N'hood Info Treatment	0.065	0.002	0.144	0.030	0.165	0.039	0.119	0.058	0.052	0.073
	(0.055)	(0.084)	(0.084)	(0.068)	(0.095)	(0.095)	(0.087)	(0.069)	(0.060)	(0.070)
N'hood Info Treatment × Left-wing		0.090								
		(0.107)								
N'hood Info Treatment × University			-0.130							
			(0.121)							
N'hood Info Treatment × Renter				0.070						
				(0.103)						
N'hood Info Treatment × Above Med Inc					-0.157					
					(0.108)					
N'hood Info Treatment × Above Age 45						0.040				
						(0.127)				
N'hood Info Treatment × Married							-0.129			
							(0.123)			
N'hood Info Treatment × Religious								0.010		
								(0.128)		
N'hood Info Treatment × Foreign Born									0.076	
									(0.182)	
N'hood Info Treatment × Female										-0.026
										(0.108)
Sum of Treatment Effects		0.092	0.014	0.100	0.008	0.080	-0.010	0.068	0.127	0.047
Dep Var Mean (Non-std)	0.452	0.452	0.452	0.452	0.452	0.452	0.452	0.452	0.452	0.452
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
R2	0.055	0.039	0.040	0.027	0.031	0.028	0.028	0.027	0.027	0.027
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
Indiv Controls	X	X	X	X	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X	X	X	X	X

Notes: This table explores heterogeneity in the effects of the neighborhood information treatment on preferences for redistribution. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. The heterogeneity dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table D7: Neighborhood information treatment and preferences for redistribution (heterogeneity)

	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N'hood Info Treatment	0.071	0.032	0.150	0.013	0.179	-0.041	0.050	0.063	0.078	0.019
	(0.044)	(0.110)	(0.085)	(0.069)	(0.090)	(0.070)	(0.067)	(0.053)	(0.054)	(0.074)
N'hood Info Treatment		0.055								
× Left-wing		(0.132)								
N'hood Info Treatment			-0.147							
× University			(0.109)							
N'hood Info Treatment				0.098						
× Renter				(0.108)						
N'hood Info Treatment					-0.185					
× Above Med Inc					(0.102)					
N'hood Info Treatment						0.191				
× Above Age 45						(0.104)				
N'hood Info Treatment							0.013			
× Married							(0.109)			
N'hood Info Treatment								-0.023		
× Religious								(0.101)		
N'hood Info Treatment									-0.175	
× Foreign Born									(0.177)	
N'hood Info Treatment										0.081
× Female										(0.111)
Sum of Treatment Effects		0.087	0.004	0.111	-0.006	0.150**	0.064	0.040	-0.097	0.100
Dep Var Mean (Non-std)	6.601	6.601	6.601	6.601	6.601	6.601	6.601	6.601	6.601	6.601
Dep Var SD (Non-std)	2.302	2.302	2.302	2.302	2.302	2.302	2.302	2.302	2.302	2.302
R2	0.189	0.181	0.076	0.072	0.077	0.073	0.071	0.071	0.072	0.072
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
Indiv Controls	X	X	X	X	X	X	X	X	X	X
N'hood Controls	X	X	X	X	X	X	X	X	X	X

Notes: This table explores heterogeneity in the effects of the neighborhood information treatment on preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Sample is restricted to individuals having answered correctly to both attention check questions and having spent at least 20 seconds (corresponding to the 5th percentile) in the treatment question page before submission. The heterogeneity dimensions explored are left-wing ideology, university education, rental status, income (above and below 1,144 EUR per month), age (above and below age 45), marital status, religiosity, origin (foreign-born or not), and gender (female or male). Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG (r = 350). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

E Additional robustness

E.1 Space LNG

Tables E1 and E2 replicate the results from Table 3 using LNG (space) instead of LNG (value). Results are qualitatively analogous, but the estimates' magnitude and precision are significantly smaller. These suggest that local inequality in living space is less relevant than local inequality in housing values.

E.2 Weighted LNG

Tables E3 and E4 replicate the results from Table 3 using a version of the (value) LNG that weights different dwellings differently depending on the distance to the origin. I use the variable $WLNG$, defined as follows:

$$WLNG(r) = Gini(A(r), W(d, r)) \tag{4}$$

where *Gini* is the Gini function, $A(r)$ is the set of dwellings defining the local neighborhood of a building of reference. A depends on the parameter r and is defined as previously described in Section 2.1. $W(d, r)$ is a matrix of weights associated with each dwelling. The weights in W can be defined in different ways. In this instance, I assign a dwelling a weight of 0 if its distance to the building of reference, d, is greater or equal than r. I assign a weight of $(r - d)/r$ otherwise. That is, the weight decays linearly with distance. This version of the LNG responds to the rationale that what is close might be more relevant, and therefore should be assigned a higher weight.[15]

Results using the WLNG are qualitatively analogous to those from Table 3, but they are slightly more precise. These are consistent with the idea that the very immediate local environments are more relevant in shaping perceptions and demand for redistribution.

E.3 Interaction with information treatments

The survey contained a second information experiment presented after eliciting respondents' perceived national-level income distribution and inequality and before the demand for redistribution questions. The treatment is a replication of Cruces et al. (2013), where a fraction of respondents are informed about their actual position in the income distribution (shock in perceived relative income). A concern is that interactions with the information treatments could partly drive some of the main results presented in the paper. The first treatment, presented before eliciting perceptions and demand for redistribution, could have affected both outcomes of interest. The second treatment could have had an impact on the demand for redistribution. This section presents replications of the paper's main tables, including an interaction with the information treatments when appropriate.

Descriptive results: Tables E5 and E6 report estimates of the following models:

$$PercGini_i = \beta_1 LNG(r)_i + \beta_2 LNG(r)_i \times InfoT1_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{5}$$

$$PrefRed_i = \beta_1 LNG(r)_i + \beta_2 LNG(r)_i \times InfoT1_i + \beta_3 LNG(r)_i \times InfoT2_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{6}$$

[15]The basic LNG can be re-interpreted as a special case of the WLNG, where all dwellings with $d \leq r$ are assigned a weight of 1.

where $InfoT1$ is an indicator taking the value of 1 if the respondent was exposed to the first information treatment.[16] $InfoT2$ is an indicator if the respondent was exposed to the second information treatment.[17] The rest of the variables are defined as in Equation 1.

Local inequality is still positively related to perceived inequality, and the association is still stronger in narrowly defined neighborhoods. Column 8 in Table E5 shows that a one SD increase in the LNG is associated with 7.3% of a SD increase in *Perceived Gini* (1.3 points, 3% of the mean) among untreated individuals. The information treatment does seem to slightly increase the influence of the LNG, as the total effect for treated individuals ($\beta_1 + \beta 2$) is 12.5% of a SD at $r = 200$ (5% of the mean).

The association with demand for redistribution is still close to zero. Among untreated individuals (β_1), the effect is insignificant but mildly positive. Both information treatments seem to negatively impact demand for redistribution, particularly the second. The total effect on treated individuals ($\beta_1 + \beta 2 + \beta 3$) is negative, particularly when r is large.

Quasi-experimental results: Tables E7 and E8 report estimates of the following models:

$$PercGini_i = \beta_1 Treated_i + \beta_2 Treated_i \times InfoT1_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{7}$$

$$PrefRed_i = \beta_1 Treated_i + \beta_2 Treated_i \times InfoT1_i + \beta_3 Treated_i \times InfoT2_i + X_i^{'}\gamma + \delta_{i(j)} + \epsilon_i \tag{8}$$

Where $InfoT1$ and $InfoT2$ are defined as before. $Treated$ is defined as in Section 5 and identifies individuals exposed to new apartment buildings. X and δ are defined as in Equation 2.

Exposure to new apartment buildings increases perceived inequality. Column 2 shows that (survey) untreated individuals exposed to a new building perceive 14.3% of a SD more inequality (about 6% of the mean). The effect is significantly larger among untreated homeowners (Column 10). Untreated renters see essentially no change in perceptions (Column 8). Exposure to the first information treatment partly magnifies these effects. Column 2 shows that those treated in the survey and exposed to a new building perceive 25.2% more inequality (10% of the mean).

The positive effect on demand for redistribution is significantly stronger among untreated respondents. Participants exposed to the second information treatment demand less redistribution when exposed to a new building. Columns 1-6 show increases in demand for redistribution ranging between 17-30% of a SD (6-12% of the mean). The effects are especially strong among homeowners (Columns 9-10). Respondents exposed to the second information treatment significantly demand less redistribution (24-40% of a SD less). Thus, the total effect on demand for redistribution ($\beta_1 + \beta 2 + \beta 3$) is generally negative when taking the interaction with the second information treatment into account.

The previous results suggest that the interaction between the information treatments and exposure to a new building is relevant, particularly when studying the effects on demand for redistribution.

[16]Described in Appendix D. In the tables the variable is called *N'hood Info Treatment*.
[17]In the table, the variable is called *Rel Income Info Treatment*.

Table E1: Local inequality (LNG) (space) and inequality perceptions

	Perceived Gini											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG (Space)	0.046	0.055	0.029	0.006	-0.053	-0.095	0.046	0.051	0.015	-0.005	-0.084	-0.126
	(0.037)	(0.044)	(0.043)	(0.043)	(0.049)	(0.053)	(0.041)	(0.050)	(0.048)	(0.049)	(0.055)	(0.052)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
R2	0.009	0.009	0.008	0.007	0.008	0.009	0.056	0.056	0.055	0.055	0.056	0.058
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table explores the relationship between local and perceived inequality. All continuous variables are standardized. Perceived inequality is measured with *Perceived Gini*, constructed as described in Section 3.2. Local inequality is measured using the (space) Local Neighborhood Gini (LNG), which captures inequality in dwelling space in narrowly defined neighborhoods, constructed as described in Section 2.3. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E2: Local inequality (LNG) (space) and preferences for redistribution

	Preferences for Redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG (Space)	0.032	-0.004	-0.007	-0.027	-0.056	-0.027	0.034	0.009	0.005	0.009	-0.001	0.027
	(0.042)	(0.039)	(0.039)	(0.040)	(0.040)	(0.043)	(0.037)	(0.040)	(0.048)	(0.050)	(0.052)	(0.053)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339
R2	0.012	0.011	0.011	0.011	0.012	0.011	0.186	0.185	0.185	0.185	0.185	0.185
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows the relationship between local inequality and preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Local inequality is measured using the (space) Local Neighborhood Gini (LNG), which captures inequality in dwelling space in narrowly defined neighborhoods, constructed as described in Section 2.3. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E3: Local inequality (WLNG) and inequality perceptions

	Perceived Gini											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WLNG	0.063	0.082	0.068	0.044	-0.002	-0.038	0.058	0.087	0.077	0.053	0.003	-0.041
	(0.034)	(0.034)	(0.034)	(0.034)	(0.036)	(0.040)	(0.035)	(0.036)	(0.035)	(0.035)	(0.037)	(0.042)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
R2	0.010	0.011	0.009	0.008	0.007	0.008	0.057	0.059	0.057	0.056	0.055	0.056
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table explores the relationship between local and perceived inequality. All continuous variables are standardized. Perceived inequality is measured with *Perceived Gini*, constructed as described in Section 3.2. Local inequality is measured using the (weighted) Local Neighborhood Gini (WLNG), which captures inequality in dwelling value in narrowly defined neighborhoods. The WLNG assigns lower weights to dwellings farther away from respondents' dwelling. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E4: Local inequality (WLNG) and preferences for redistribution

	Preferences for Redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WLNG	0.040	-0.007	-0.049	-0.073	-0.107	-0.114	0.032	0.015	-0.006	-0.014	-0.031	-0.037
	(0.045)	(0.044)	(0.039)	(0.036)	(0.033)	(0.034)	(0.045)	(0.045)	(0.040)	(0.040)	(0.034)	(0.033)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339
R2	0.012	0.011	0.012	0.013	0.016	0.016	0.186	0.185	0.185	0.185	0.185	0.186
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows the relationship between local inequality and preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Local inequality is measured using the (weighted) Local Neighborhood Gini (WLNG), which captures inequality in dwelling value in narrowly defined neighborhoods. The WLNG assigns lower weights to dwellings farther away from respondents' dwelling. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E5: Local inequality (LNG) and perceived inequality — Interactions with information treatment

	Perceived Gini											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG	0.053	0.081	0.026	-0.037	-0.081	-0.105	0.037	0.074	0.021	-0.030	-0.069	-0.091
	(0.039)	(0.037)	(0.039)	(0.037)	(0.042)	(0.045)	(0.039)	(0.037)	(0.041)	(0.039)	(0.041)	(0.044)
N'hood Info Treatment	0.021	0.024	0.044	0.076	0.075	0.063	0.048	0.054	0.076	0.103	0.097	0.078
$\times$ LNG	(0.052)	(0.048)	(0.048)	(0.049)	(0.047)	(0.047)	(0.052)	(0.048)	(0.049)	(0.049)	(0.048)	(0.050)
LNG Total Effect	0.074	0.106	0.070	0.039	-0.006	-0.042	0.085	0.127	0.097	0.073	0.028	-0.012
	(0.046)	(0.044)	(0.045)	(0.044)	(0.050)	(0.053)	(0.047)	(0.042)	(0.042)	(0.042)	(0.047)	(0.051)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447	0.447
Dep Var SD (Non-std)	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178
R2	0.010	0.012	0.009	0.009	0.009	0.010	0.056	0.059	0.056	0.056	0.055	0.055
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table explores the relationship between local and perceived inequality. All continuous variables are standardized. Perceived inequality is measured with *Perceived Gini*, constructed as described in Section 3.2. Local inequality is measured using the Local Neighborhood Gini (LNG), which captures inequality in dwelling values in narrowly defined neighborhoods, constructed as described in Section 2.3. *N'hood Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the first information treatment. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E6: Local inequality (LNG) and preferences for redistribution — Interactions with information treatments

	Preferences for Redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG	0.084	0.005	-0.023	-0.035	-0.066	-0.043	0.069	0.020	0.008	0.014	-0.001	0.017
	(0.061)	(0.054)	(0.054)	(0.052)	(0.049)	(0.050)	(0.056)	(0.049)	(0.049)	(0.048)	(0.043)	(0.044)
N'hood Info Treatment	-0.026	-0.033	-0.058	-0.071	-0.080	-0.080	0.000	0.008	-0.009	-0.028	-0.037	-0.047
$\times$ LNG	(0.042)	(0.044)	(0.045)	(0.044)	(0.044)	(0.045)	(0.041)	(0.046)	(0.049)	(0.048)	(0.047)	(0.046)
Rel Income Info	-0.085	-0.049	-0.025	-0.030	-0.031	-0.036	-0.079	-0.058	-0.050	-0.055	-0.066	-0.069
Treatment $\times$ LNG	(0.050)	(0.049)	(0.047)	(0.049)	(0.053)	(0.054)	(0.044)	(0.043)	(0.043)	(0.045)	(0.049)	(0.049)
LNG Total Effect	-0.027	-0.077	-0.106	-0.136	-0.177	-0.159	-0.009	-0.030	-0.051	-0.069	-0.104	-0.098
	(0.046)	(0.042)	(0.038)	(0.037)	(0.040)	(0.045)	(0.046)	(0.041)	(0.039)	(0.035)	(0.037)	(0.043)
r (meters)	100	200	350	500	750	1000	100	200	350	500	750	1000
Dep Var Mean (Non-std)	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565	6.565
Dep Var SD (Non-std)	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339	2.339
R2	0.014	0.013	0.014	0.016	0.019	0.017	0.186	0.184	0.184	0.185	0.186	0.186
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
Indiv Controls							X	X	X	X	X	X
N'hood Controls							X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows the relationship between local inequality and preferences for redistribution. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Local inequality is measured using the Local Neighborhood Gini (LNG), which captures inequality in dwelling values in narrowly defined neighborhoods, constructed as described in Section 2.3. *N'hood Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the first information treatment. *Rel Income Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the second information treatment. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, and left-wing parties' vote share in the 2015 national elections. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E7: New apartment building treatment and perceived inequality — Interactions with information treatment

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.162	0.131	0.187	0.167	0.130	0.090	0.000	-0.075	0.234	0.192
	(0.094)	(0.101)	(0.106)	(0.111)	(0.123)	(0.124)	(0.155)	(0.132)	(0.117)	(0.129)
N'hood Info Treatment	0.100	0.108	0.082	0.087	0.144	0.144	0.331	0.466	-0.027	-0.033
× New Building Treatment	(0.125)	(0.134)	(0.149)	(0.164)	(0.165)	(0.183)	(0.198)	(0.190)	(0.153)	(0.179)
Bldng Treat Total Effect	0.261	0.239	0.269	0.253	0.274	0.233	0.331	0.391	0.207	0.159
	(0.099)	(0.100)	(0.106)	(0.120)	(0.116)	(0.132)	(0.183)	(0.154)	(0.107)	(0.121)
Dep Var Mean (Non-std)	0.441	0.441	0.435	0.435	0.436	0.436	0.449	0.449	0.437	0.437
Dep Var SD (Non-std)	0.176	0.176	0.173	0.173	0.176	0.176	0.177	0.177	0.176	0.176
R2	0.018	0.071	0.020	0.071	0.020	0.067	0.042	0.169	0.021	0.062
N	937	937	704	704	586	586	301	301	636	636
Indiv Controls		X		X		X		X		X
N'hood Controls		X		X		X		X		X
District FE	X	X	X	X	X	X	X	X	X	X
Years in Dwelling	5+	5+	10+	10+	15+	15+	5+	5+	5+	5+
Sample	Full	Full	Full	Full	Full	Full	Renters	Renters	Owners	Owners

Notes: This table shows the effects of the new apartment building treatment on perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). *N'hood Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the first information treatment. The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Columns 3-6 further restrict the sample to individuals who have lived same dwelling since at least 2010 or 2005. Columns 7-10 further restrict the sample to include only either renters or homeowners. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

Table E8: New apartment building treatment and preferences for redistribution — Interactions with information treatments

	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.283	0.177	0.311	0.237	0.345	0.262	0.098	0.041	0.363	0.234
	(0.113)	(0.104)	(0.132)	(0.123)	(0.158)	(0.154)	(0.203)	(0.214)	(0.141)	(0.142)
N'hood Info Treatment	-0.044	-0.007	-0.056	-0.050	-0.072	-0.027	-0.159	-0.066	0.049	0.020
$\times$ New Building Treatment	(0.121)	(0.112)	(0.151)	(0.136)	(0.176)	(0.165)	(0.201)	(0.234)	(0.157)	(0.156)
Rel Income Info	-0.294	-0.275	-0.325	-0.317	-0.333	-0.350	0.046	0.107	-0.472	-0.457
Treatment $\times$ New Building Treatment	(0.133)	(0.126)	(0.144)	(0.139)	(0.167)	(0.160)	(0.248)	(0.236)	(0.153)	(0.153)
Bldng Treat Total Effect	-0.055	-0.105	-0.071	-0.130	-0.060	-0.116	-0.015	0.083	-0.061	-0.204
	(0.110)	(0.101)	(0.125)	(0.117)	(0.144)	(0.129)	(0.176)	(0.176)	(0.144)	(0.137)
Dep Var Mean (Non-std)	6.487	6.487	6.403	6.403	6.418	6.418	6.771	6.771	6.352	6.352
Dep Var SD (Non-std)	2.311	2.311	2.295	2.295	2.244	2.244	2.294	2.294	2.308	2.308
R2	0.018	0.183	0.033	0.193	0.036	0.164	0.020	0.170	0.037	0.215
N	937	937	704	704	586	586	301	301	636	636
Indiv Controls		X		X		X		X		X
N'hood Controls		X		X		X		X		X
District FE	X	X	X	X	X	X	X	X	X	X
Years in Dwelling	5+	5+	10+	10+	15+	15+	5+	5+	5+	5+
Sample	Full	Full	Full	Full	Full	Full	Renters	Renters	Owners	Owners

Notes: This table shows the effects of the new apartment building treatment on perceived inequality. All continuous variables are standardized. *Preferences for Redistribution* measures demand for redistribution in a scale from 0 to 10, with 10 representing the highest demand for redistribution. *New Building Treatment* is an indicator taking the value of 1 if the individual resides within 350 meters of a new apartment building (constructed in 2017-19). *N'hood Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the first information treatment. *Rel Income Info Treatment* is an indicator taking the value of 1 if the individual was exposed to the second information treatment. The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Columns 3-6 further restrict the sample to individuals who have lived in the same dwelling since at least 2010 or 2005. Columns 7-10 further restrict the sample to include only either renters or homeowners. Individual controls include age, log household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing ideology, rental status, and employment status. Neighborhood controls (at the census tract level in 2015) include population density, median apartment size (log square meters), quality, year of construction, share of foreign population, left-wing parties' vote share in the 2015 national elections, and value LNG ($r = 350$). All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis.

F Survey description

F.1 Overview

The online survey was conducted by Netquest from May 28, 2020, to June 9, 2020. I instructed Netquest to recruit participants from all neighborhoods and districts across the city, while attempting to maintain representativity in terms of gender, age, and socio-economic status to the extent possible. Each participant was compensated independently on completion status as per the company policy, although full payments were only awarded for completed surveys. Compensation for an estimated 15-minute long survey was approximately 3 USD (paid in "koru points"), a virtual currency. The median completion time was 18 minutes.

In total, 1,444 respondents completed the survey. 99 of them had to be discarded as they could not be matched to a valid address.[18] Also, 15 additional observations were dropped due to inconsistencies between individual responses and Netquest's records about the respondent (e.g., the gender or age of the participant did not match). The final sample includes 1,330 participants.

The survey can be accessed from the following link:
https://bostonu.qualtrics.com/jfe/form/SV_d0TvD2V8DV8tzWl.

F.2 Address matching

I matched addresses using a fuzzy string matching algorithm in R. I first cleaned the addresses from the Cadastre and those typed by respondents in the survey by removing non-content words (e.g., "de", "la", "d'en"). Using the Levenshtein distance as a criterion, I then matched each survey address to the closest match in the Cadastre (within a ZIP Code). I could exactly match (distance of 0) approximately 75% of the addresses. I randomly checked a small fraction of those to verify the quality of the match. I manually checked those not exactly matched (distance greater than 0). Among those, a relevant fraction (10-15%) was finally assigned to the closest matched addresses. On many occasions, a typo was the reason for not obtaining an exact match in the first place. I had to manually match the rest of the addresses (about 10%). The most common reasons for not obtaining an exact or close match were: (1) typos in the address; (2) clear typos in the ZIP code; (3) use of an unofficial name for a street (e.g., the street "Gran via de les Corts Catalanes" is commonly known as "Gran via").

F.3 Attrition

Survey attrition was 24%. Attrition was slightly larger than what Netquest originally anticipated (20%), but in accordance with figures from other studies.[19] As in Kuziemko et al. (2015), attrition was not random. Female, older, and lower socioeconomic status individuals were significantly less likely to complete the survey.

F.4 Pilot survey and adaptation to COVID-19

Before the main online survey, I conducted a small pilot survey in Amazon Mechanical Turk ($N = 141$). Jobs were posted on that platform from March 13 to April 9, 2020. Respondents received 1.5 USD for completing

[18]The most common reasons were: the participant introduced a ZIP code from outside Barcelona, typos in the address, and the inexistence of the address.

[19]For example, Kuziemko et al. (2015) reported an attrition rate of 22% in their online survey.

a survey with an expected completion time of approximately 15 minutes (the median completion time was 11 minutes). Participants had to be registered in Spain and reside in Barcelona or Madrid to participate in the survey. That survey can be accessed from the following link:
https://bostonu.qualtrics.com/jfe/form/SV_8fdYYvX7RuTRcRD.

All the survey's main questions were already present in the pilot. Most of the changes and new questions involved adapting the survey to the COVID-19 pandemic. Spain was amidst a strict lockdown since mid-March and until June 20th, overlapping with the survey. It became essential to adapt the questions and wording of the pilot survey to the new circumstances. Two experts in survey design from the University of Southern California Center for Economic and Social Research helped me adapt the survey. The list below contains a summary of the main guidelines I followed in the adaptation process:

- Minimize to the extent possible the use of the word COVID to avoid potential priming.
- Household income question: do not ask about current income. Ask about income earned during 2019 instead.
- Unemployment question: add COVID as a reason for unemployment.
- On several questions (e.g., commuting and social interactions): explicitly ask before and after COVID. Make sure the question is well-adapted to the pandemic (e.g., add "work from home" as an option in the commuting question).

F.5 Survey questions (English translation)

1. How many individuals (including you) live in your dwelling?
2. How many adults (including you) live in your dwelling?
3. Approximately, what was your personal annual gross income* (before taxes and transfers) in 2019? **Income includes: Wages before taxes, Pensions, Unemployment benefits, Interests, Rental Income, Dividends. Does not include: Social Assistance (example: housing subsidies)*
4. Also approximately, what was the gross annual income* (before taxes and transfers) of your household in 2019? **Income includes: Wages before taxes, Pensions, Unemployment benefits, Interests, Rental Income, Dividends. Does not include: Social Assistance (example: housing subsidies)*
5. [50% of the sample] The following table shows the average price of a dwelling* in each of the 10 districts of Barcelona: [Table — see Figure D1]
   (a) Which district has, on average, the *most expensive* dwellings? *Ciutat Vella/Eixample/Sants-Montjuïc/Les Corts/Sarrià-Sant Gervasi/Gràcia/Horta-Guinardó/Nou Barris/Sant Andreu/Sant Martí*
   (b) Which district has, on average, the *cheapest* dwellings? *Ciutat Vella/Eixample/Sants-Montjuïc/Les Corts/Sarrià-Sant Gervasi/Gràcia/Horta-Guinardó/Nou Barris/Sant Andreu/Sant Martí*
6. [Pyramid Diagrams] These five diagrams show different types of society. Please read the descriptions and look at the diagrams and decide which you think best describes Spain. What type of society is Spain? Which diagram best describes Spain currently? *Type A. A small elite at the top, very few people in the middle and the great mass of people at the bottom./ Type B. A society like a pyramid with a small elite at the top, more people in the middle, and most at the bottom. / Type C. A pyramid except that just a few people are at the bottom. / Type D. A society with most people in the middle. / Type E. Many people near the top, and only a few near the bottom.*

7. You previously indicated that the gross annual income of your household in 2019 was EUR € and that there are N adults in your household. This means that the gross income per adult in your household was EUR € per month. Based on this information: What do you think was the share of Spanish households with an income per adult below yours in 2019?

8. [Scale Representation] Now imagine a scale ranging from 0 to 100, in which the poorest individuals and households of Spain are located in 0, and the richest in 100. In this question, we want to know what is, in your opinion, the level of income of different households located at different points in that scale. For example, if we ask you about the household located at position 10, we want to know what is, in your opinion, the level of income of that household, considering that being in position 10 means that 9% of the Spanish households would have an income below that amount, while the rest (90%) would have an income above that amount. In your view, what was, in 2019, the gross monthly income (before taxes) per adult per household in the position. . . ? *(For your reference, the gross monthly income per adult in your household is EUR € per month)*

    (a) Position 10: .... (Euros per Month)
    (b) Position 30: .... (Euros per Month)
    (c) Position 50: .... (Euros per Month)
    (d) Position 70: .... (Euros per Month)
    (e) Position 90: .... (Euros per Month)
    (f) Position 99: .... (Euros per Month)

9. Now we continue using the same scale, but we will now restrict the geographical scope to your neighborhood. That is, to answer this question, think only on the families and households from your neighborhood. [Image of Scale] In particular, imagine a scale ranging from 0 to 100, in which the poorest individuals and households of your neighborhood are located in 0, and the richest in 100. In your view, what was, in 2019, the gross monthly income (before taxes) per adult of the household in the 50th position in this scale? *(For your reference, the gross monthly income per adult in your household is EUR € per month) .... (Euros per Month)*

10. [50% of the sample] The income per adult in your household is EUR € per month. [Image of Scale highlighting position]
    In the previous question, you indicated that you believed that ... % of the Spanish households had an income below your household in 2019. According to the most recent data from the Instituto Nacional de Estadística (INE), your household is among the poorest/richest ...% of household in Spain. These households have an income per adult below EUR € per month. Therefore, your perception was correct/incorrect.

11. Some people think that public services and social benefits should be improved, even at the expense of paying higher taxes (on a scale from 0 to 10, these people would be at 0). Others think that it is better to pay less taxes, even if this means having fewer public services and social benefits (these people would be at 10 in the scale). Other people are in between. In which position would you place yourself?

12. How much income redistribution (through taxes and transfers from the state) would you like to see in Spain? No redistribution, 0 in the scale, means that the state does not redistribute any income. Maximum redistribution, 10 in the scale, means that, after the redistribution, everyone has exactly the same level of income.

13. Suppose that you were in charge of spending the taxpayers money collected by all the public administrations in the country (city councils, regions and central government). In normal circumstances*, what share of the budget do you think that should be spent on...? Please enter the percent of the budget you would assign to each spending category. Note that the total must sum 100. *We refer to the situation before the arrival of coronavirus (COVID-19) in Spain.

    (a) Defense and national security (police, army etc.) : ...

    (b) Infrastructure (roads, trains, airports, etc.) : ...

    (c) Education (public schools and universities) : ...

    (d) Social security: Retirement pensions : ...

    (e) Social security: Unemployment benefits, disability pensions, other subsidies to the poor : ...

14. Generally, to what extent do you consider yourself happy or unhappy? Please, use a scale from 0 to 10, where 0 means “completely unhappy” and 10 “completely happy”.

15. On a scale from 0 to 10, where 0 means “no trust at all” and 10 means “absolute trust”, to what extent do you trust in politicians in general?

16. Some people think that economic status depends almost exclusively on effort, education and professional value (on a scale from 0 to 10, these people would be at 0). Other people think that what really matters is the family origin, connections or simply luck (these people would be at 10 on the scale). In your opinion, what is the most important factor determining economic status in Spain?

17. [Scale Representation] Imagine a scale ranging from 0 to 100, where in 0 there are the poorest persons and households in Spain, whereas the richest persons and households are in 100. Now think, for a moment, in your family and in the household in which you grew up. In particular, think about the financial situation of your household when you were a small kid. At that time, where do you think your household was located in this scale? Please, respond by sliding the bar below. [Slider]

18. [Scale Representation] Imagine a scale ranging from 0 to 100, where in 0 there are the poorest persons and households in Spain, whereas the richest persons and households are in 100. In 10 years, where do you think your household will be in this scale? Please, respond by sliding the bar below. [Slider]

19. Now think of a child born in a very poor household, among the 20% poorest households in the country.

    (a) [Scale Representation] What do you think is the probability that this child, after growing up and forming a family, will still be part of the 20% poorest households in the country?

    (b) [Scale Representation] What do you think is the probability that this child, after growing up and forming a family, will become part of the 20% richest households in the country?

20. When talking about politics, it is common to use the expressions “left” and “right”. On a scale from 0 to 10, where 0 means “very left-wing” and 10 “very right-wing”, where would you place yourself?

21. Could you please tell me which party did you vote for in the last national elections (November 2019)? *PSOE/PP/VOX/Podemos/Ciudadanos/ERC/JxCat/CUP/Other/Did not vote/NA*

22. How de you define yourself in terms of religiosity? *Catholic/Religious but not Catholic/Not religious/Agnostic/Atheist/NA*

23. In normal circumstances*, how often do you meet with the following groups of people? (We refer to a meeting to chat, drink something, do some activity) * We refer to the situation previous to the arrival of COVID-19 in Spain [Table with options]

    (a) Family: *Almost every day/Several Times a week/Several times a month/Once a month/Several times a year/Once a year/Never*

    (b) Childhood Friends: *Almost every day/Several Times a week/Several times a month/Once a month/Several times a year/Once a year/Never*

    (c) Friends from college or other circles: *Almost every day/Several Times a week/Several times a month/Once a month/Several times a year/Once a year/Never*

    (d) Neighbors: *Almost every day/Several Times a week/Several times a month/Once a month/Several times a year/Once a year/Never*

    (e) Colleagues from work: *Almost every day/Several Times a week/Several times a month/Once a month/-Several times a year/Once a year/Never*

24. After the arrival of coronavirus (COVID-19) in Spain, in March 2020, how have your interactions with the following groups of people changed? (We refer to interactions outside work in person, even if in some meters of distance, or remotely, by telephone or video call)

    (a) Family: *Much less frequent/Somewhat less frequent/Substantially unchanged/Somewhat more frequent/Much more frequent*

    (b) Childhood Friends: *Much less frequent/Somewhat less frequent/Substantially unchanged/Somewhat more frequent/Much more frequent*

    (c) Friends from college or other circles: *Much less frequent/Somewhat less frequent/Substantially unchanged/Somewhat more frequent/Much more frequent*

    (d) Neighbors: *Much less frequent/Somewhat less frequent/Substantially unchanged/Somewhat more frequent/Much more frequent*

    (e) Colleagues from work: *Much less frequent/Somewhat less frequent/Substantially unchanged/Somewhat more frequent/Much more frequent*

25. Among your friends and work colleagues, would you say that there are individuals from all social classes or, in the contrary, most of them are either working class, middle class, or upper class? *There are individuals from all social classes/ Most of them are working class/ Most of them are middle class/ Most of them are upper class*

26. Do you have an account in any of the following social networks? Social networks: Facebook, Twiter, Tuenti, LinkedIn, Instagram. *Yes/ No*

27. [if answered yes to the previous question] In normal circumstances*, how often do you use some of the previous social networks? Social networks: Facebook, Twiter, Tuenti, LinkedIn, Instagram * We refer to the situation previous to the arrival of COVID-19 in Spain. *Everyday/ 5-6 days per week/ 3-4 days per week/ 1-2 days per week/ Almost never*

28. In normal circumstances*, how often do you get informed about the current events? (For example, by watching the news on TV, reading the newspaper, etc.) * We refer to the situation previous to the arrival of COVID-19 in Spain. *Everyday/ 5-6 days per week/ 3-4 days per week/ 1-2 days per week/ Never because I don't have time/ Never because I am not interested in the news*

29. [if informed] In normal circumstances*, which of the following media outlets do you regularly use to get informed about the current events? (Please, mark all the options that apply) * We refer to the situation previous to the arrival of COVID-19 in Spain. *TV/ Radio/ Newspapers/ Internet/ Other*

30. Basic demographic information

    (a) Gender: *Male/ Female*

    (b) Year of Birth:

    (c) Country of Origin:

31. Civil Status: *Married/ Single/ Widow/ Separated/ Divorced/ NA*

32. How many children do you have? *0/ 1/ 2/ 3/ More than 3*

33. What is the highest educational degree that you ever completed? *Did not go to school/ Went to school less than 5 years/ Primary school/ Secondary school/ Professional degree/ University degree/ NA*

34. Which of the following situations best describes you currently? *Works (private sector)/ Works (public sector)/ Works (self-employed)/ Unemployed and previously worked/ Unemployed and looking for the first job/ Student/ Retired or Pensioner/ Domestic work/ Other*

35. [if employed] What is your main occupation at the firm or organization you work for? Please, choose the option that best describes your job. If you have multiple jobs, choose the one that best describes your main occupation. *Directors and managers (example: CEOs, financial directors, restaurant managers)/ Technicians and health or education professionals (example: doctors, veterinarians, pharmacists, professors, teachers) / Other technicians and professionals of science (example: physicists, geologists, biologists, engineers, architects, lawyers, system analysts, economists) / Technicians and support professionals (example: draftsmen, commercial representatives, programmers) / Office workers not attending the general public (example: accountants, librarians) / Office workers attending the general public (example: receptionists, teleoperators, bank tellers) / Workers in restaurants and other establishments (example: waiters, shop assistants, cashiers) / Health services workers (example: nurses, nannies, hairdressers, tour guides, driving instructors) / Protection and security service workers (example: police, firefighters, private security, lifeguards) / Qualified workers in agriculture, fishing or forestry sectors/ Qualified workers in construction (example: builders, carpenters, plumbers, painters)/ o Qualified workers in the manufacturing industry (example: welders, smiths, mechanics, electricians, bakers, shoemakers, tailors)/ Fixed machinery operators (example: miners, operators of machines in textile industry)/ Drivers and operators of mobile machinery (example: train conductor, bus drivers, truck drivers)/ Non-qualified workers in the service sector (example: domestic workers, vehicle cleaners, kitchen helpers, garbage collectors)/ Pawns in agriculture, fishing, construction, manufacturing or transportation industry/ Military occupations*

36. [if unemployed] How many months have you been unemployed?

37. [if unemployed] What was the main reason for you to stop working? *Layoff/ Contract termination/ Disease or own disability/ Studies or formation/ Family reasons (e.g., childcare)/ Coronavirus (COVID-19) (e.g., the firm had to temporarily shut down)*

38. [if unemployed] What was your main occupation at the firm or organization you worked for? Please, choose the option that best describes your last job. If you had multiple jobs, choose the one that best describes what was your main occupation. [list of occupations — same as previous question]

39. [if employed] For how many years have your worked in this job?

40. [if unemployed] How many years did you work in your last job?
41. [if employed] Before COVID-19, How did you usually commute to work? *Public transportation/ Taxi/ Private Vehicle/ Walking/ I work from home*
42. [if employed] How do you currently commute to work? *Public transportation/ Taxi/ Private Vehicle/ Walking/ I work from home*
43. [if unemployed] When you worked, how did you used to commute to work? *Public transportation/ Taxi/ Private Vehicle/ Walking/ I worked from home*
44. [if unemployed with no previous experience or if studies] When you studied, how did you used to commute to the study center? *Public transportation/ Taxi/ Private Vehicle/ Walking/ I studied from home*
45. [if employed] In which district or city is your current job or study center located? Please, respond to the first question if you work or study in Barcelona. Respond to the second question if you work or study outside Barcelona.
    (a) If you work or study in Barcelona,In which city district is your current job or study center located? *Ciutat Vella/ Eixample/ Sants-Montjuïc/ Les Corts/ Sarrià-Sant Gervasi/ Gràcia/ Horta-Guinardó/ Nou Barris/ Sant Andreu/ Sant Martí*
    (b) If you work or study outside Barcelona, In which municipality is your current job or study center located? ...
46. [if unemployed] In which district or city was your last job or study center located? Please, respond to the first question if you worked or studied in Barcelona. Respond to the second question if you worked or studied outside Barcelona.
    (a) If you worked or studied in Barcelona, In which city district was your job or study center located? *Ciutat Vella/ Eixample/ Sants-Montjuïc/ Les Corts/ Sarrià-Sant Gervasi/ Gràcia/ Horta-Guinardó/ Nou Barris/ Sant Andreu/ Sant Martí*
    (b) If you worked or studied outside Barcelona, In which municipality was your job or study center located? ...
47. What share of the population in Spain do you think are immigrants? ... %
48. What share of the population in your neighborhood do you think are immigrants? ... %
49. We're almost done! To conclude, we'd like to ask you a few questions regarding your dwelling. Thanks for your collaboration! Please, could you indicate the address of your dwelling?
    (a) City: *Barcelona*
    (b) Type of road: *Calle/ Avenida/ Rambla/ Plaza/ Ronda/ Travesía/ Paseo/ Carretera/ Pasaje/ Urbanización*
    (c) Name of the road:
    (d) Number:
    (e) ZIP:
50. For how many years have you lived in this dwelling?

51. The dwelling in which you live is. . . ? *Owned, completely paid/ Owned, with pending payments/ Owned, obtained from an inheritance or donation/ Rental/ Ceded for free or at a low price from a relative, firm, etc./ Social Rental*

52. Approximately, what is the size of your dwelling?

53. [if owner] Did you buy this dwelling? *Yes/ No*

54. [if renter] Did you rent this dwelling? *Yes/ No*

55. [if owner that purchased the dwelling] What are the main reasons for which you purchased this dwelling in this neighborhood? (Please, select all options that apply) *Proximity to work or the study center/ Proximity to the dwelling of a relative/ Neighborhood amenities (schools, parks, etc.)/ Type of neighbors/ Price of the dwelling/ Good connection with public transportation/ The neighborhood is safe*

56. [if renter] What are the main reasons for which you rented this dwelling in this neighborhood? (Please, select all options that apply) [same options as in the previous question]

57. [if did not rent or buy the dwelling] What are the main reasons for which you live in this dwelling in this neighborhood? (Please, select all options that apply) *Proximity to work or the study center/ Proximity to the dwelling of a relative/ Neighborhood amenities (schools, parks, etc.)/ Type of neighbors/ Price of the dwelling/ Good connection with public transportation/ The neighborhood is safe/ It is the dwelling of my partner/spouse / it is/was the dwelling of a close relative (father or mother)*

58. When you were 16, did you live in this same dwelling? *Yes/ No*

59. You indicated that you used to live in a different dwelling when you were 16 years old. Could you please provide the address of that dwelling? This is the last question of the survey. If you can give us this address, we would be extremely grateful to you. If you cannot because you feel uncomfortable or do not remember it, then you do not need to answer this question. Please, accept our apologies if this question made you feel uncomfortable.

    (a) City:

    (b) Type of road: *Calle/ Avenida/ Rambla/ Plaza/ Ronda/ Travesía/ Paseo/ Carretera/ Pasaje/ Urbanización*

    (c) Name of the road:

    (d) Number:

    (e) ZIP: