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

JOB MARKET PAPER

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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 first 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 then elicit inequality perceptions and preferences for redistribution from an original large-scale survey conducted in Barcelona. I link those to respondents' specific LNG and local environments using exact addresses, observed in the survey. Finally, I identify the causal effects of neighborhoods using two different approaches. The first is an outside-the-survey quasi-experiment that exploits within-neighborhood variation in respondents' recent exposure to new apartment buildings. The second is a within-survey experiment that induces variation in respondents' information set about inequality across neighborhoods. I find that local environments significantly influence inequality perceptions but only mildly affect demand for redistribution.

Keywords: Inequality, Gini, Redistribution, Housing
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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. 2012; 2018a). Perceptions may be subjective, but they ultimately impact policy.

Local environments are likely to shape perceptions. Neighborhoods are key 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). Our knowledge about the origin of perceptions may still limited, but it is reasonable to expect neighborhoods also to influence them (Hauser and Norton 2017).

Local inequality may directly influence beliefs about inequality, and therefore also affect preferences for redistribution. The connection through neighborhoods is intuitive, and recent research provides suggestive evidence in its favor (Cruces et al. 2013, Minkoff and Lyons 2019, Xu and Garand 2010). However, establishing causality is challenging. Individuals' locations are not random, and their beliefs about inequality and redistribution could substantially weigh in their 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 combine two different identification strategies with 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).

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 can then compute the LNG, a measure of local inequality specific to *each* building in my sample.

I conducted an original large-scale online survey in Barcelona to elicit inequality perceptions and demand for redistribution. To measure perceived inequality, I build from Eriksson and Simpson (2012) and Chambers et al. (2014) by estimating respondents' perceived income distribution and compute the implied Gini. I measure demand for redistribution from an adaptation of a question in the General Social Survey (GSS), in which respondents face the trade-off between public services and social benefits and taxes. The survey records participants' exact addresses, which allows me to link individual responses to their dwelling-specific estimate of local inequality (i.e., the LNG) and other neighborhood characteristics. Consequently, the survey provides the 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 but not with demand for redistribution. The relationship is strongest restricting the attention within 200 meters of respondents' dwellings, when one additional standard deviation (SD) in LNG translates into a 4% increase in perceived inequality, and it remains positive within 500 meters. The association with demand for redistribution is negligible and, if anything, negative. Nevertheless, results also show 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 play a role as well.

I exploit quasi-experimental variation *within* neighborhoods induced by the recent rise of new apartment buildings to get at causality. 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 a 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 (2.5% more). The effects are robust to several variations in the baseline empirical specification. They are also unlikely to be driven by individuals sorting into the neighborhood before the treatment or by individuals leaving the area following the new building's construction.

I complement the previous approach to identification by using an embedded experiment within the survey designed to shock respondents' information set about local inequality *across* neighborhoods. The survey setting guarantees pure randomization of the treatment exposure across participants, thereby credibly identifying its effects on perceptions and demand for redistribution. The treatment shifts perceived inequality and demand for redistribution by approximately 2%, but effects are not significant. I also document that the statistically zero effect masks significant heterogeneity along some dimensions — most importantly, education, income, origin, and district of residence. I argue that results are consistent with the hypothesis that what is close is more relevant.

Collectively, results confirm that local environments significantly influence perceived inequality and (to a lesser extent) demand for redistribution. Effects are stronger when exploiting variation from narrowly defined neighborhoods, highlighting the importance of the spatial dimension in determining, at least, beliefs about inequality.

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).

This paper actively contributes to this strand of research in two ways. First and foremost, it 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 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. This work's underlying motivation is the idea that perceptions could (potentially) be as important in the decision-making process as the actual objects they are built upon. Initially, the focus was mostly placed on mobility perceptions — or prospects for upward mobility (POUM), in the terminology of the literature (Benabou and Ok 2001, Piketty 1995). However, there has been a significant widening in the array of objects studied as potential drivers in recent years. Among others, these have included 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. 2018, 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 of this paper to this strand of work is on three fronts. First, it 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 mostly descriptive and typically combines a wide variety of data 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, Martínez-Toledano 2020, Piketty and Saez 2003; 2006; 2014). In more recent years, the attention has shifted towards a more local measurement of inequality, with a particular focus on cities (Fogli and Guerrieri 2019, Glaeser et al. 2009). The reason for the shift is likely a

[1] For example, in Buenos Aires, Cruces et al. (2013) showed that perceived income rank at the national level was 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 (latter) paper "shocks" local environments by randomizing the presence of a luxury car in South Africa (poor-looking person in Boston) in a field experiment. Both papers measure demand for redistribution using respondents' support for a tax on millionaires.

combination of the increased availability of high-quality readily-usable data for research and the recognition that social interactions and 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 of all, the LNG is truly 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 analysis over time (Openshaw and Taylor 1979, Wong 2009). Secondly, this is the first paper that primarily uses geolocated real estate data to construct a measure of inequality. This particular type of data is precisely what enables independence from administrative boundaries. Thirdly, the LNG can be interpreted as a measure of local housing consumption inequality. For welfare, one could argue that we ultimately care about consumption. Also, housing typically represents a large fraction of total household expenditures, and, relative to other forms of consumption, its definition is likely to be more stable over time. Thus, the LNG is informative about inequality in a relevant aspect of living standards. Lastly, the LNG is a measure that is, by construction, easily harmonized and replicable across contexts. Similar data exists in countries outside Spain, and its nature guarantees a high degree of homogeneity across settings.[3]

The rest of the paper is organized as follows. Section 2 formally introduces the LNG and outlines the steps to construct it using the Spanish real estate administrative data. Section 3 describes the sample and the design of the survey. Section 4 explores the descriptive association between local environments, perceptions, and demand for redistribution. Section 5 gets at causality by exploiting the variation in local neighborhoods induced by new apartment building constructions. Section 6 exploits the within-survey experiment as a complementary approach to identification. Finally, Section 7 concludes.

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

2.1 The spatial distribution could matter: intuition

Local inequality could be a critical determinant of inequality perceptions. To provide intuition for the LNG and this hypothesis, consider the two abstract Cities depicted in Figure A1 — City 1 and City 2. Each polygon represents a dwelling. The number in its interior represents the value (or size).

First of all, 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, it must be the case that any measure of inequality will describe both cities as equally unequal. For example, computing a standard Gini index would yield a value of 0.167. Let us now look at the two dwellings colored in

[3] The key elements required to construct the LNG are the exact location of the real estate and some information about its characteristics (e.g., size), and these leave very little room for arbitrary definitions.

dark-green at both cities' eastern border. 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 — defined as the set of immediately adjacent dwellings (and colored in light-green) — is apparent. While all the neighboring dwellings in City 1 are of the same value, those in City 2 are not. We can see this very clearly by computing the Gini index of these two dwellings' local neighborhoods, delivering values of 0 and 0.167 in City 1 and 2, respectively.

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 would be reasonable to think that each dwelling's local neighborhood plays a significant role in determining inequality perceptions. Citywide inequality would be completely irrelevant. After all, a household in one corner of the city could only know about another household located in the opposite corner through close neighbors' interactions. Of course, in reality, individuals are not immobile, and they certainly interact with others outside their immediate neighborhood. However, as long as they spend some fraction of their time at home,[4] or as long as interactions of some form occur at the neighborhood level, the previously outlined mechanism should play some role.[5]

2.2 The Local Neighborhood Gini (LNG)

The LNG captures a dimension of housing inequality in the immediate local environment of a dwelling. To construct it, one first has to decide on the relevant dimension of inequality to study. The choice set will depend on the data available. Given the type of information required to construct the LNG (geolocated real estate data), housing space is likely to be a common element in this set. Housing values could also be a natural option if observed. Secondly, one has to decide on the spatial scope of the neighborhood or, in other words, on how "local" a local neighborhood ought to be. The LNG defines a local neighborhood as the set of properties contained within an r-meter buffer around the dwelling.[6] The application at hand should guide the choice. The LNG is simply the Gini index of that local neighborhood.

2.3 Construction in practice: data

Spanish 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 that is maintained and regularly updated by the Spanish Ministry of the Treasury for

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

[5]This is indeed the case. 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.

[6]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 had to ultimately rely on aggregated data (e.g., at the census tract level). The LNG is based on geolocated housing data and, therefore, can circumvent this problem.

taxation purposes.[7] 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), and the primary use (e.g., residential, retail, or cultural). The data also contains the GIS cartography available for each municipality in the country, with all the real estate precisely geolocated. The dataset is updated twice per year by the Ministry of the Treasury, usually in February and August, and it offers a precise snapshot of the real estate in the country at the time of the update. All the information previously described is publicly available.[8] The complete data also contains information on the owner of every property and its estimated market value (*valor catastral*). However, this information is restricted.

With the Cadastre data alone, it is possible to compute the LNG capturing dispersion in dwelling space. However, I was also interested in obtaining an additional estimate of inequality in dwelling value — probably closer to traditional wealth inequality. To that end, I merged the Cadastre data with real estate transactions data from the Catalan Tax Agency (*Agència Tributària de Catalunya*, ATC).

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 between homeowners and new buyers. This tax only applies to transfers of used property.[9] During this period, over 275,000 transactions occurred, 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 makes it possible to easily link the Cadastre and the ATC data and assign a price tag to all the dwellings transferred in this period.[10] Unlike the Cadastre, this dataset is confidential.[11]

Other data sources: In the dwelling value estimation process, I complemented the previous two sources with demographic data 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).

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

[8] The data can be downloaded at https://www.sedecatastro.gob.es/.

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

[10] 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 the other information available in the ATC. Namely, the year of construction/renovation, quality of the unit, and size (square meters).

[11] It was first used in Garcia-López et al. (2020). Access is granted by the ATC subject to their approval.

2.4 Construction in practice: 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.[12] The prediction made use of the roughly 65,000 real estate transactions that occurred in Barcelona in 2009-19. I combined the ATC data with all the information from the census, registry, and other sources — 157 variables in total — to implement the random forest.[13] The prediction error (Out of Bag Root Mean Squared Error, OOBRMSE) of the algorithm was 0.1437.[14] The most important variable in the prediction (by a magnitude of almost 3) was the dwelling's size (square meters). Other variables with a 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,[15] and the year of construction.

2.5 Construction in practice: methodology

I construct the LNG in five steps. First, a building plot in a city is selected.[16] Second, r is chosen, and a buffer with an r meter radius is drawn from the plot's centroid. The present research question calls for a small r. However, the intention was to let the data speak on how local a local neighborhood ought to be. Thus, I constructed the LNG for several buffers, ranging from 100 meters to one kilometer. In the third step, all the plots whose centroids intersect with the buffer are selected. All the *dwellings* in these plots constitute the building's "local neighborhood". This step is illustrated in Figure 1. In the fourth step, the Gini index for the local neighborhood is computed, thus summarizing the dispersion in dwelling values (or sizes) in the area surrounding the selected plot. This is the LNG of the plot.[17] Finally, steps one through four are repeated for every plot in every city considered. Figure 2 illustrates the variation in LNG for the iconic Eixample neighborhood in the city of Barcelona. Figure A2 shows the variation in the entire city.

2.6 The LNG compared to income inequality in Spanish cities

Table B1 provides a comparison between different inequality measures defined at the city level (whenever possible). In that table, *Income Gini* is the standard Gini coefficient calculated from

[12]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).

[13]At first, with no parameter tuning. The process was then repeated, implementing some tunning. 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.

[14]Other studies predicting house values achieved OOBRMSEs of 0.12-0.16 (Čeh et al. 2018, Fan et al. 2006, Mullainathan and Spiess 2017). Therefore, the performance of my prediction is slightly inferior to those. This underperformance is likely to be explained by the fact that the number of rooms in the dwelling (a variable with typically a high explanatory power) is not observed in the Cadastre.

[15]*Apartment quality* is a categorical variable capturing the overall quality of a unit (in a scale from 1 to 10).

[16]A plot is the area underneath a building.

[17]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.

the 2018 *Encuesta de Condiciones de Vida* (ECV) microdata.[18] 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 in the ATC data.

The first take away from the table is that 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 theoretically unbounded and more volatile than dwelling sizes (and therefore possibly dwelling values too). Second, space is scarce in cities, even when 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).

The second main takeaway is that citywide value/space inequality is above the mean LNG. To interpret this result, it is helpful to go back to the toy example in Figure A1. In that example, both cities have a City Gini of 0.167, but they substantially differ in their Mean LNG. While the Mean LNG is 0.161 in City 2, the respective value is only 0.091 in City 1, or about 43% smaller. The reason for that discrepancy lies in the differential spatial distribution of dwellings within the city or, in other words, in the differential level of residential segregation. Local inequality and segregation are essentially two sides of the same coin (Glaeser et al. 2009). 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 present in the city.

3 The survey

3.1 Sample

Netquest, a market-research company based in Barcelona, carried out sample recruitment. Field work 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).[19] Given the nature of the research questions, 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. However, 114 of them had to be discarded due to different

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

[19] The final median completion time was 18 minutes. Netquest compensated all respondents participating in the survey, even if not completing it, as a way to maintain the high-quality of its online panel.

reasons.[20] The final sample includes 1,330 individuals.[21]

Table 1 shows the comparison between the Netquest sample and the target population in Barcelona. The sample is reasonably well-balanced in terms of age, marital status, rental status, employment status, and household characteristics, but not so much in terms of gender (males overrepresented), origin (foreign-born are underrepresented), education (university graduates are overrepresented),[22] and ideology (left-wing individuals are overrepresented).[23] Table B2 shows the geographical distribution of the sample across districts and neighborhoods. Representation across all districts and neighborhoods was achieved, and its geographic balance is good. However, 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?"

The choice of the question responds to two reasons. First and foremost, this is the adaptation of a question in the General Social Survey (GSS) that others have previously used to study distributional preferences (e.g., Alesina and Giuliano 2011).[24] The specific adaptation was carried out by the sociologists working at the Spanish *Centro de Investigaciones Sociológicas* (CIS) and has been used in several of their surveys, including the *Encuesta Social General Española*, an adaptation of the entire GSS survey in the Spanish context. Therefore, this question allows for a good framing of results in the context of the existing literature.[25] Second, translating survey questions to different languages can be problematic at times due to information potentially lost in translation or to misleading wording. Having a suitable option already translated into the Spanish language was an important motivation for the choice.

[20] Ninety-nine because they 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. Fifteen because some inconsistencies between their responses and Netquest's records were detected (e.g., in the gender or age of the participant).

[21] The survey can be accessed from the following link:
https://bostonu.qualtrics.com/jfe/form/SV_d0TvD2V8DV8tzWl. Appendix D contains a detailed description of the entire survey and the complete list of questions translated in English.

[22] Note that this statistic comes from the 2011 census, and therefore the imbalance is probably not so exaggerated.

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

[24] 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?"*.

[25] Values from the question were rescaled so that a 10 represents maximum demand for redistribution.

Perceived inequality: I measure perceived inequality by eliciting respondents' perceived income distribution first. I then compute the implied Gini coefficient of the distribution. Figure 3 shows the question used. Specifically, after explicitly defining income and indirectly introducing the notion of income distribution in two previous questions,[26] 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. 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.[27]

I chose to elicit the income (and not wealth) distribution for the following reasons. First, describing income is more straightforward and 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. In contrast, very few individuals file for the wealth tax.[28] 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 4 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 (*Encuesta de Condiciones de Vida*, 2018). Nonetheless, it is the case that incomes are substantially overestimated at the top of the distribution — particularly in the percentiles 90 and 99.[29] Figure 4 strongly suggests that respondents' took the question seriously and that answers contain meaningful information.

Figure 5 shows the distribution of perceived inequality in the sample. The mean (median) *Perceived Gini* is 0.45 (0.42), above the actual Gini (0.36). The main source of discrepancy is the substantial overestimation of income at the top.[30]

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

[27]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.

[28]The reason for that is a high minimum exemption threshold, currently set at 700,000 euros of net wealth. Very few individuals or households surpass it, to the extent that, in 2018, there were only 77,397 wealth tax filers in Catalonia (Agencia Tributaria 2018b). In contrast, also in Catalonia in 2018, there were 3,655,487 income tax filers (Agencia Tributaria 2018a).

[29]Chambers et al. (2014) also document substantial overestimation of incomes at the top.

[30]In Appendix C, I explore heterogeneity on perceived income and inequality along the observable characteristics of respondents.

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 significantly perceive more inequality. District fixed effects do not seem to matter. For example, relative to a right-wing individual, left-wingers perceives approximately 25% of a SD more inequality (4.5 points, 10% of the variable mean).[31] This result is consistent with Chambers et al. (2014), which finds that (in the US) liberals significantly perceive more inequality.[32] To the best of my knowledge, no existing studies show how inequality perceptions correlate with other individual characteristics. Therefore, I cannot compare my results with a benchmark.

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 in 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 smaller (about five times smaller). These findings are consistent with previous research (Gimpelson and Treisman 2018, Niehues 2014). The direction in 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 typically less willing to redistribute in AG11).[33] Table B3 studies the relationship between *Preferences for Redistribution* and other major drivers according to the literature. All correlations have the expected sign, and inequality perceptions appear to be among the most prominent determinants.

Overall, the correlations presented in the table are consistent with our knowledge about beliefs on inequality and demand for redistribution.[34]

[31] *Left-wing* is an indicator taking a value of 1 if the individual responded a 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?"*.

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

[33] Although not shown in the table, this is 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.

[34] Appendix C explores heterogeneity on these two variables along several individual characteristics.

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:

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

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 controls that include age, log household income, household size, and indicators for female, foreign-born, college education, married, religious, left-wing ideology, home-renter, and unemployed. $\delta_{i(j)}$ is an indicator taking the value of 1 if individual i resides in district j. Finally, standard errors are clustered at the neighborhood level.[35]

Table 3 shows the OLS estimates of Equation 1 with the definition of local neighborhoods (characterized by r) broadening across columns, ranging from a 100 meters buffer around the respondent's dwelling and up to one kilometer. The first (last) six columns show the estimates without (with) controls. Figure 6 plots the same regressions coefficients to better visualize the pattern that emerges in the table.

In narrowly defined neighborhoods ($r \leq 500$), the relationship between LNG and perceived inequality is positive. 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). These results mean that more *actual* (local) inequality is associated with more *perceived* (aggregate) inequality, consistent with the idea of individuals extrapolating from local environments. Also, the decaying pattern suggests that what is close is more relevant.

Comparing the results with and without controls does not yield significantly different conclusions. Keeping r fixed, the β estimate obtained with or without controls is virtually unchanged. Thus, 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. That does not imply that unobservables are irrelevant, but the little movement in the estimates after the inclusion of controls points in that direction (Oster 2019).

Preferences for redistribution: Table 4 studies the relationship between local inequality (LNG) and distributional preferences by re-estimating Equation 1 with *Preferences for Redistribution* as dependent variable. The structure of this table is analogous to Table 3. Figure 7 plots the regression coefficients.

There is a mild negative relationship between the level of aggregation at which the LNG is defined (captured by r) and preferences for distribution, similarly to Table 3. In this instance,

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

though, the relationship between the two is only mildly positive (and not significant) when $r = 100$. By expanding the spatial scope of the neighborhood (r), the association quickly flips signs.

The results are not inconsistent 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*. 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 (0.0014) is actually contained within a 95% confidence interval of the point estimate in Column 8.[36] 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 Table 4.[37]

The inclusion of controls matters, especially in broadly defined neighborhoods. When r is small, the difference in a given column comparison (with and without controls) is not statistically significant. However, when $r > 500$, the difference between becomes apparent. Specifically, the relationship between local inequality and redistribution preferences, when no controls are included, is negative and precisely estimated. This suggests that sorting might be playing a role in this instance. I explore this hypothesis in Table B4, 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 B4 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.[38] However, as the definition of local neighborhoods widens, 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 of the sorting, Column 5 ($r = 750$) implies that, in a local neighborhood that is 1 SD more unequal than average (+4.7 points in LNG), left-wing individuals are approximately 13.5% *less* likely to be represented. This finding is consistent with left-wing individuals disliking inequality more than conservatives (Napier and Jost 2008), and suggests the presence of significant sorting along this characteristic. Importantly, left-wing individuals are generally more in favor of redistribution (Table 2). Therefore, not controlling for this individual

[36]This is also true for the rest of the estimates in the last six columns. These would be: 0.008, 0.0014, 0.008, 0.0031, -0.003, -0.0074.

[37]Sands and de Kadt (2019), in the context of South Africa, construct a measure of income inequality aggregating the census tracts contained within 500 meters to one kilometer around the dwellings of their respondents. They find that 1 SD increase in their local inequality measure is associated with a 0.8pp (a small effect). Also similar to this paper, they find that aggregations above one kilometer yield a negative relationship.

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

characteristic biases the estimates in Table 4 downwards.[39]

Overall, results show a positive association between local and perceived inequality, but virtually no relationship between local inequality and demand for redistribution. Furthermore, the latter appears to be (if anything) negative, mainly when local neighborhoods are broadly defined and when ideology is not taken into account. That may seem a counterintuitive result, but it is partly explained by residential sorting along ideology. Consequently, there are reasons to be skeptical of the simple correlations (particularly regarding demand for redistribution). To get at causality, it is necessary to find a setting with exogenous variation in local inequality. This paper explores two avenues. First, within-neighborhoods variation generated from the rise of new apartment buildings (in the next section). Second, between-neighborhoods experimental variation generated from a shock in the information set about local inequality (in Section 6).

5 Quasi-experimental approach: new building treatment

5.1 Identification and empirical strategy

The first approach to shocking local environments exploits within-neighborhood variation caused by the rise of new apartment buildings close to respondents' homes. Figure 8 illustrates the intuition behind this approach to identification in an extreme but clear example. 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 that building (and in the one just behind) are relatively 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. The reader will note that, most 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 in that year jumped to 0.23 — representing a tenfold increase relative to 2012. Based on the stark contrast between the two buildings, the new construction is likely to disrupt the way dwellers in the older building see their neighborhood. This 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 built in the previous three years before being surveyed (2017, 2018, or 2019). X_i and $\delta_{i(j)}$ are defined as in Equation 1.

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

Figure 9 offers a visualization of the identification strategy. It shows a map of Barcelona divided by its ten districts. A red symbol represents the exact location of a new apartment constructed in 2017-19. The orange circumferences surrounding each symbol represent a 350-meter buffer around a new construction. All individuals in the sample located 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 any unobservable characteristic of individuals within a district. If that holds, then β causally identifies the effect of new constructions on the outcomes of interest — perceptions and redistribution preferences.

Identification is plausible. The treatment exploited in this setting is the rise of a new *apartment* building. It is not the construction of new museums, churches, or other iconic buildings. Tens of apartment buildings are constructed every year all across the city. Moreover, to address the potential threat of individuals strategically locating in neighborhoods that are "improving" faster over time relative to others in the city (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 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, individuals residing in the area close to a new building are likely to notice it, but that is probably not true for those living significantly farther.

The three-year treatment time-window responds to small clusters of new constructions that appear over short periods. Over extended horizons (5-10 years), new constructions are scattered all across the city. However, as Figure 9 makes clear, a local neighborhood treated in 2019 is also likely to have been treated in 2018 or 2017. Thus, defining an individual as untreated when a new apartment was constructed close by just one year earlier might bias the treatment effects downwards if those persist longer than one year.

New building treatment and local inequality: Table 5 investigates the effects of the treatment on local inequality. Given that dwelling prices are estimated from real estate transactions on *used* (i.e., not new) properties,[40] 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.[41] 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. This is true for both

[40] See Section 2.4.

[41] Even when *Year of Construction* is one of the variables included in the estimation algorithm. To accurately predict the value of a newly constructed dwelling, transaction data on new dwellings should be incorporated into the estimation sample.

value and space, but the shift is only significant for space. In terms of the magnitude, baseline results (in Columns 2 and 4) suggest that being exposed to a new apartment building increases local inequality in value (space) by approximately 8% (32%) of a SD. These roughly translate into +0.73 (+0.26) percentage point increase in the LNG, or 6% (130%) of the mean.[42] The effects are not too different 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 B5 shows that both groups are not significantly different in terms of any observed characteristic.

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

Perceived inequality: Table 6 investigates the effects of the new apartment building treatment on perceived inequality. Across the table, odd columns show the estimates of some variation of Equation 2 without the battery of controls. Even columns include controls.

Exposure to a new apartment building increases perceived inequality. Column 2 (the baseline specification) shows an average treatment effect of approximately 17% 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 seems implausible. By applying these restrictions, the magnitude slightly increases to 17-20% of a SD, translating into an increase of 3-3.5 points in *Perceived Gini*. Therefore, 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 along rental status. The rationale is that, relative to renters, moving costs are likely to be substantially higher among homeowners (e.g., they might have a mortgage).[43] We should therefore be less worried about this concern in the homeowners sample. Results in these last columns suggest slightly stronger effects among homeowners — although point estimates across columns are neither qualitative nor statistically different from each other. The treatment effect is stable around 17% of a SD. Estimates in Columns 7 and 8 are less precise due to the significantly smaller renters sample relative to homeowners. Hence, results are inconsistent with large displacement effects.

Preferences for redistribution: Table 7 investigates the effects of the new apartment building treatment on preferences for redistribution. It has the same structure as Table 6.

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 the demand for redistribution by approximately 7% of a SD (0.16 points, or 2.5% of the mean). However, the

[42] As argued earlier, the effects on local value inequality are likely to represent a lower bound.
[43] 42% of homeowners in the sample have pending payments on their dwelling.

coefficient is not statistically significant. The following columns investigate the result's sensitivity by further restricting the sample to individuals having resided in the same dwelling for longer or to either renters or homeowners alone. Consistently across columns, results show mildly positive effects of the treatment, but reaching a 10% significance level at most. Therefore, evidence suggests a small effect of the treatment on preferences for redistribution, but zero effects cannot be ruled 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 10 and 11 offer a quick snapshot of the section by summarizing results in specification curves.

Alternative distance thresholds and identification strategies: Figure A3 illustrates the alternative 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. Thus, 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 located 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 leave all individuals that are not in its interior out of the sample. These correspond to the small circumferences colored in black. This same approach, or variations of it, has previously been 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. Therefore, I explore the three of them while varying the different threshold distances (inner and outer ring) from 200 meters to one kilometer.

Tables B6 (*Perceived Gini*) and B7 (*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, evidence strongly suggests that 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, evidence suggests a mild positive effect of the treatment on preferences for redistribution. Estimates range from 1.7% of a SD (Column 2 in Panel B) to 28% of a SD (Column 6 in Panel C), which would translate into an increase ranging from 0.3 to 0.6 points in *Preferences for Redistribution*. In most instances, zero effects cannot be ruled out. However, estimates consistently exhibit a positive sign. Third, the comparison of Panels B and C suggests the presence of spillover effects. This is especially clear comparing estimates from Columns 1 and 2 in Panel B with those from the rest of the table. 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 more than 200 meters. Based on the positive and significant estimates in the rest of the columns, that assumption seems challenged.

Alternative distance thresholds and time-windows: The baseline specification considers an individual as 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 B8 (perceived inequality) and B9 (preferences for redistribution) show the results of this exercise. Panel A replicates the baseline results, where an individual is considered treated if exposed to a new building in the past three years (from 2017). Panels B and C restrict the three-year time window to a two-year and one-year, 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 treatment *before* the time-window considered (from 2017). In practice, this means that, in Panel C, individuals exposed to a treatment in either 2017 or 2018 are excluded. In Panel B, individuals exposed to a treatment in 2017 are excluded. No further restriction is applied in Panel A.[44] The rationale for these further restrictions is to test the hypothesis that treatment effects do not immediately vanish. If that is the case, then estimates in specifications that include individuals previously treated (odd columns) should systematically be smaller.

Results in both tables provide supporting evidence of a shift in perceived inequality and of a milder shift in preferences for redistribution. Besides, they suggest treatment effects are not short-lived. The latter point is most evident when comparing odd and even columns in Panel C from both tables. In the six possible comparisons across the two tables, the even column's coefficient is always larger. Moreover, 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 treatment time window) — although the differences between odd and even columns are not that stark. Overall, this exercise suggests average treatment effects are somewhere between 4 and 24% of a SD (translating into $+0.7$ to $+4.2$ points in *Perceived Gini*).

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

Regarding preferences for redistribution, the shift is between 4 and 16% of a SD (translating into $+0.09$ to $+0.36$ points in *Preferences for Redistribution*).

IV: Tables B10 and B11 present results following an IV approach, where I instrument recent variation in LNG using the new apartment building shock. As Table 5 already hinted, results using Δ*LNG (Value)* are noisy due to a weak first stage, so I will focus the discussion on Δ*LNG (Space)* (Columns 5-8 in both tables).

IV estimates support 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). That suggests the presence of a 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 20% of a SD increase in *Preferences for Redistribution* (0.44 points, 7% of the mean). These magnitudes are substantially larger than those from the reduced-form regressions (Tables 6 and 7). Thus, at face value, Tables B10 and B11 provide even stronger support to the link between local environments, perceptions, and demand for redistribution. Nevertheless, these 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.

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 10 and 11. 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.[45]

The positive effect of the treatment on perceived inequality and demand for redistribution is evident. Figure 10 shows that the estimated effect on *Perceived Gini* is positive on 317 of the 325 specifications (97.5%). It is significant at the 90% (95%) level in 173 (121) specifications. When the coefficient is negative (on eight occasions), it is never statistically different from zero. The lowest value is -0.07, and the largest is 1.32. The mean value is 0.34 — doubling the size of the baseline estimate (marker in blue). Figure 11 looks at *Preferences for Redistribution*. Coefficients are positive in 311 specifications (95.7%). They are significant at the 90% (95%) level in 80 (34) of them. When negative, they are not statistically different from zero. The lowest value is -0.06 and the largest 1.34. The mean value is 0.20 — almost tripling 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

[45] 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).

direction, but they are smaller 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 A4 shows the question. The question is rather abstract, but other papers have used in the past 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 chosen pyramid.[46] Table B12 shows the results, where I also vary distance thresholds (i.e., 200 meters in Columns 1-3, and 500 meters in Columns 7-9) and explore heterogeneity along rental status.

Results using the income ratios (in the top two panels) confirm that the treatment increases perceived inequality, and the effects do not seem to differ based on rental status. When looking at the perceived inequality inferred from the ISSP question, the picture is slightly different. While the treatment's overall effect is still positive across columns (except in Column 6, although the coefficient there is a precise zero), magnitudes are generally smaller and not significant. Moreover, Columns 1-6 suggest that the effects are significantly stronger among renters that reside very close to the new apartment building.[47] The ISSP question is probably capturing a different form of perceived inequality (other than income), which could explain the small discrepancy in the results.[48]

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 measure of demand for redistribution posed participants a trade-off between better public services and social benefits and taxes. In contrast, this question simply asks respondents about redistribution, without any clear trade-off involved in the answer.

Regarding electoral outcomes, I consider two variables. First, an indicator taking the value

[46] 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.

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

[48] 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 low (0.10).

of one if the respondent voted for a left-wing party in the November 2019 national election.[49] Second, the vote share obtained by the same left-wing parties in the same election measured at the census tract level.[50] I construct the latter variable from aggregate electoral data I 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 of which are about redistribution, and others are 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.[51] Second, it allows me to study the causal effects of increased inequality on an outcome that has direct policy implications.

Table B13 investigates the effects of the quasi-experiment on the alternative measures of demand for redistribution. When looking at aggregate electoral outcomes in Panel B, a tract is considered treated if its centroid is within 200 (Columns 1-3), 350 (Columns 4-6), or 500 (Columns 7-9) meters from a new apartment building.

The table provides additional evidence that the new apartment building treatment increases the support for redistribution among treated individuals (or in treated tracts). This conclusion holds when looking at each of the three variables considered separately. Also, only one out of the 36 coefficients presented in the table has a negative sign, and the coefficient is a precise zero (Column 6 in Panel A). There are some discrepancies in both the magnitude of the effect and the subsample that is most affected by the treatment. While renters living close to the new building appear to be very reactive to the treatment (according to *Preferences for Redistribution (No Trade-off)*), homeowners appear to respond slightly more when looking at electoral outcomes.[52] These latter results are more in line with the baseline *Preferences for Redistribution* variable. In terms of magnitudes, Column 4 shows that being exposed to the recent rise of an apartment building increases support for redistribution by 2.3% of a SD (0.06 points, or 1% of the dependent variable mean). The treatment also increases the probability of voting for a left-wing party by 3.8pp (5% of the dependent variable mean). The same column in Panel B suggests that voters in treated tracts are, on average, 6.2% of a SD (0.5pp, or about 1% of the dependent variable mean) more supportive of left-wing parties. Treatment effects on demand for redistribution are consistently small but also consistently positive.

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

[50] A census tract is an administrative area containing roughly 1,500 individuals. In the city of Barcelona, these frequently encompass one or few blocks.

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

[52] Although, in most instances, differences across the two subsamples are not statistically different.

5.4 Mechanisms and heterogeneity

Perceived income distribution: The effects on perceived inequality are driven by higher perceived income at the top. Table 8 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) shifts 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 stock of housing, new buildings are on average of better quality.[53]

Rental status: There is no evidence of heterogeneous effects based on rental status. Tables 6 and 7 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 of this taking place. A second reason to look at that particular split (although not explicitly 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). In contrast, renters become relatively poorer (their wealth is not directly affected, and rental prices are likely to go up). Therefore, I expected that the effect could 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. Overall, there is little evidence of heterogeneity. However, the effects on perceived inequality seem to be almost entirely driven by young, low-income, single, left-wing, and natives (Table C1). Within those 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 7), coefficients are also generally larger in those groups, but differences are not significant.

5.5 Discussion

All the previous results provide strong evidence of a shift in perceived inequality following the rise of a new building in respondents' local neighborhoods. The effects on demand for redistribution are small, but consistently positive.[54] As discussed in Section 4.2, these results are consistent with the relatively weak association between perceived inequality and demand for redistribution documented in Table 2. That table suggests that only a very extreme shift in local inequality would produce a sizable movement in demand for redistribution. Also, even if settings are not

[53] According to the Cadastre data and my value predictions, relative to the dwellings of treated respondents, new apartments are of higher quality in 98% of the cases. They are more spacious and more valuable in 80% of the cases.

[54] Figures 10 and 11 provide good evidence for this.

directly comparable, the present findings align with existing research.[55] Finally, with regards to mechanisms, the effects are primarily driven by higher perceived income at the top. There is overall little heterogeneity, but effects are slightly larger among young, low-income, left-wing, and Spanish-born individuals.

These findings confirm that local environments play an important role in shaping beliefs about inequality and demand for redistribution (at least mildly). Results in this section and the previous one suggest that the "relevant" spatial scope of local neighborhoods is narrow. Possibly within 500 meters of one's dwelling. In the next and final section, I explore whether information about more "distant" neighborhoods also matters.

6 Within-survey experiment: a shock in the information set

6.1 Identification and empirical strategy

The second approach to identification exploits variation in the information set about local inequality *between* neighborhoods induced by an experiment embedded in the survey. Specifically, participants had a 50% chance of being exposed to the question shown in Figure 12. The question contains a simple table showing the average price of a dwelling across Barcelona's ten districts. Treated individuals were shown the table and subsequently asked two simple attention-check questions.[56] Those that failed to answer both questions correctly are excluded from the sample.[57] I estimate the average effects of the treatment with the following model:

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

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 defined as in Equation 1. The model does not include fixed effects as the treatment does not generate variation within districts. β captures the average treatment effect.

Covariate balance: Panel B in Table B5 shows that the sample is well balanced. None of the covariates used as controls is statistically different across subsamples.

6.2 Information treatment, perceived inequality, and preferences for redistribution

Perceived inequality: Columns 1 and 2 in Table 9 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 1.2 points, or 2.5% of the mean). The effects are small

[55]For example, in a field experiment, Sands and de Kadt (2019) finds that exposure to a luxury car in the local neighborhood increases demand for redistribution by 1.9pp (not significant).

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

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

and statistically indistinguishable from zero. The coefficients are not significantly altered with the inclusion of controls.

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

Results in Table 9 show a small effect of the treatment on both outcomes. Given the findings from the previous section, at least two stories could plausibly reconcile the present results. A first possibility is that the treatment is weak, perhaps "too informational".[58] A second hypothesis is that information about more distant neighborhoods is not as relevant. In the next section, I try to disentangle both stories by digging deeper into the effects of the treatment and looking at heterogeneity.

6.3 Mechanisms and heterogeneity

Perceived income distribution: The treatment shifted the entire perceived income distribution, but slightly more in the right tail. Table 10 shows positive shifts across all percentiles ranging from six to 12% 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 9.

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 11. 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.[59]

Columns 1-2 and 5-6 replicate Table 9 and add the *Poor District* indicator. Average Treatment effects are not altered by this inclusion and remain at approximately 7% of a SD for both outcomes. 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

[58] 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).

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

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).[60] 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).[61]

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 (17% 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 B14) — 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.[62]

Other factors: I study heterogeneity along other observables in Tables C3 and C4, in the Appendix explicitly devoted to studying heterogeneity.

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

There is probably not a single story rationalizing all these heterogeneities. However, one that seems consistent is that those 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).[63]

[60]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.

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

[62]This result is consistent with previous research (e.g., Cruces et al. 2013, Sands 2017).

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

6.4 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 effectively shift perceptions (Kuziemko et al. 2015). However, the previous section documented a clear shift in the perceived income distribution of respondents (Table 10) and significant heterogeneity that depended on the district of residence (Table 11) and other individual characteristics (Tables C3 and C4). These findings 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.

7 Conclusions

In this paper, I investigated the link between local neighborhoods, inequality perceptions, and preferences for redistribution by combining two identification strategies with survey and administrative data from Barcelona.

Neighborhoods significantly affect beliefs about inequality. They also (mildly) influence demand for redistribution. Both the descriptive and quasi-experimental approaches yielded similar conclusions, but the clearest results came from the latter. In particular, exposure to a new apartment building is associated with an average shift in *Perceived Gini* of approximately 3 points (7% of the mean). The effect on demand for redistribution is smaller (about 2.5% of the mean in *Preferences for Redistribution*). The information treatment, that affected respondents' information set about local inequality across (and not within) neighborhoods, did not significantly affect neither perceptions nor demand for redistribution — except in the less affluent districts, possibly as a consequence of the treatment making respondents' relative position salient (Cruces et al. 2013, Sands 2017, Sands and de Kadt 2019). I argued that this discrepancy in the results was consistent with the idea that what is more relevant.

The first implication of this research arises from the finding that individuals systematically misperceive inequality. Perceptions can be as important as facts in driving individuals' decisions. Thus, misguided perceptions could lead to suboptimal policies. Those ought to be corrected. That is undoubtedly a challenging endeavor for policymakers, but this work suggests a 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 from the *representative* neighborhood (i.e., those that look less like the country as a whole). Misperceptions are likely to be worse in those places.

In light of the research showing that inequality is associated with a worsening in subjective well-being (Kuhn et al. 2011, Luttmer 2005, Oishi et al. 2011, Perez-Truglia 2020), the second implication of this work is that policymakers should carefully think about the welfare of residents in gentrifying neighborhoods. Gentrification (through the proliferation of new development projects) is likely to increase residents' perceived inequality and possibly negatively impact their subjective well-being. Policymakers could address this specific externality, for instance, by temporarily subsidizing residents or by investing in the renovation of the existing stock of housing. A tax on new developments could fund the policy.

Another implication of the present findings is that granularity in the measurement of objects matters, as local environments are relevant. The LNG represents a significant contribution in this regard, as its granularity and flexibility are properties likely to appeal well beyond academic audiences. For example, policymakers could use it when planning the ideal location for a new apartment complex in a city. Finally, the LNG also paves the way to explore alternative facets of inequality (e.g., living space). Aggregation can mask significant heterogeneities. Future research can uncover them by digging deeper into the spatial dimension.

This paper has provided evidence that individuals extrapolate from their local environments when forming their beliefs (at least about inequality). Other channels, such as exposure to media, are likely to also play a role in shaping perceptions (Diermeier et al. 2017, Hauser and Norton 2017, Kim 2019). Future work should characterize the complete set of drivers and, eventually, quantify each of them' relative weight. Finally, this paper was exclusively focused on inequality. Whether local environments also shape beliefs about other types of perceptions (e.g., immigration or social mobility) remains an open question for future research.

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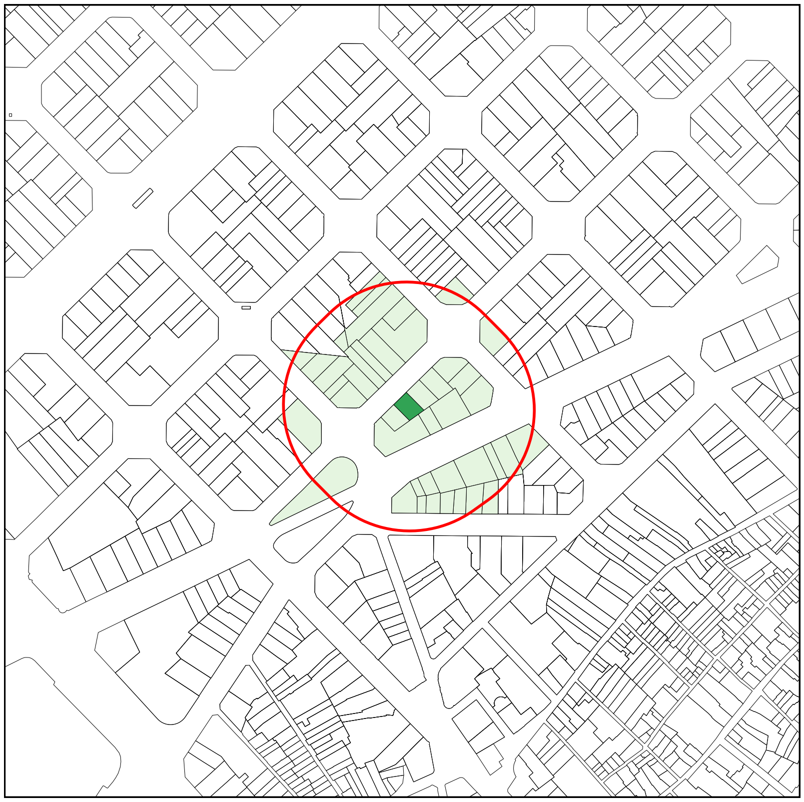


Figure 1: Defining local neighborhoods

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 2.5 for the details on the LNG construction process. Cartography from the Eixample district in the city of Barcelona. Source: Spanish Cadastre.

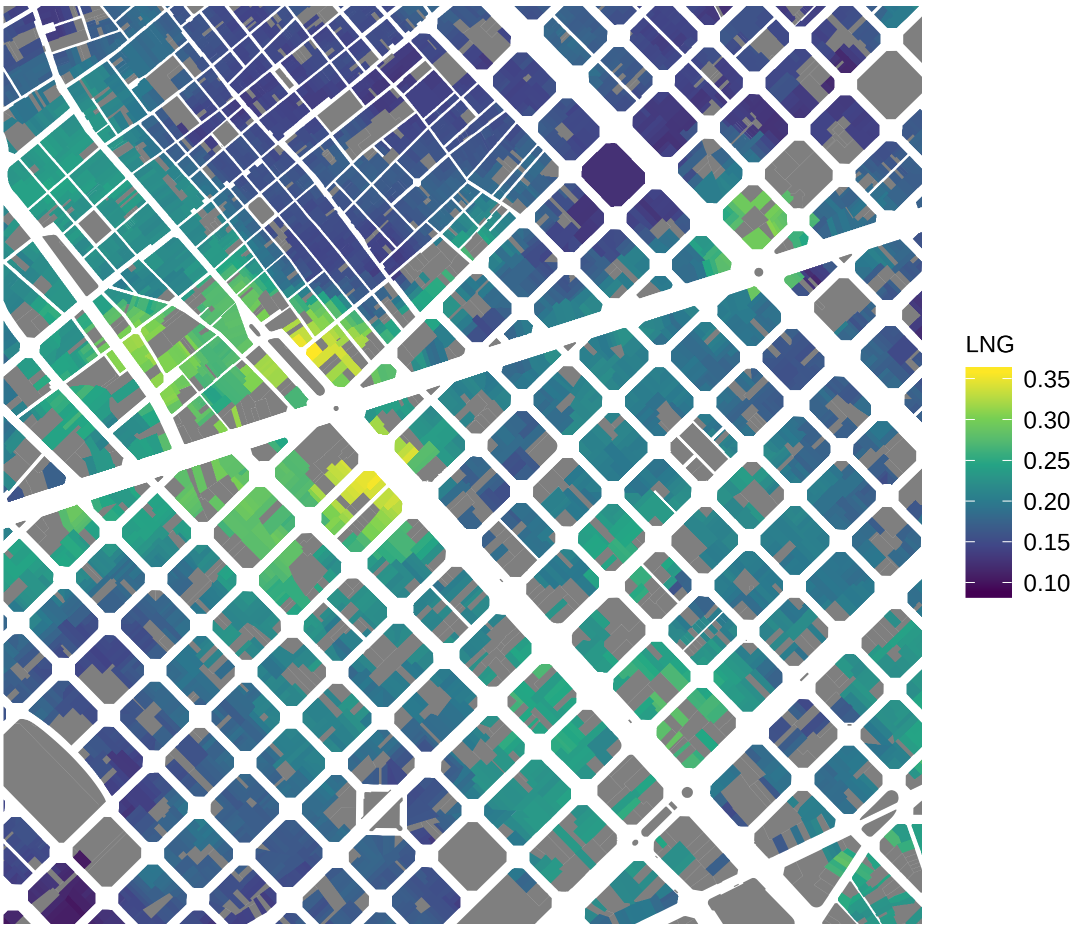
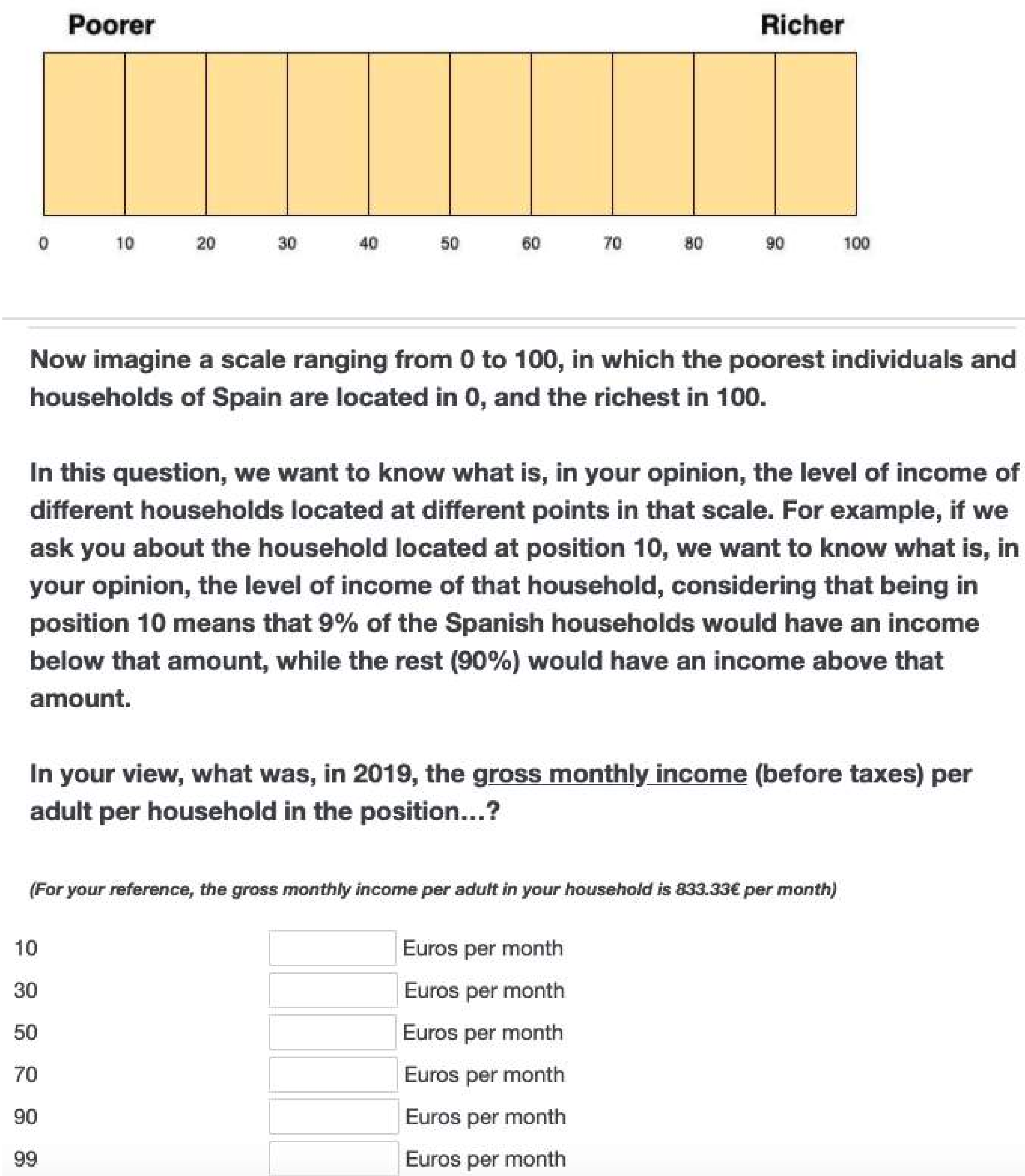


Figure 2: The Local Neighborhood Gini (LNG) in Barcelona's Eixample district ($r = 100$)

Notes: This figure shows the Local Neighborhood Gini (LNG) in the Eixample district of Barcelona. Each apartment building's local neighborhood comprehends the set of dwellings contained within an r-meter buffer (here $r = 100$) with origin in the apartment building's centroid. See Section 2.5 for the details on the LNG construction process. The LNG in this specific figure captures inequality in dwelling value. Lighter plots correspond to buildings with more unequal local neighborhoods. Darker plots correspond to buildings with more homogeneous local neighborhoods. Gray plots correspond to buildings without any dwelling in them (e.g., schools, hospitals, office buildings).



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 3: Screenshot of the survey 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. Previous 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 explicitely define income and introduce the notion of an income distribution.

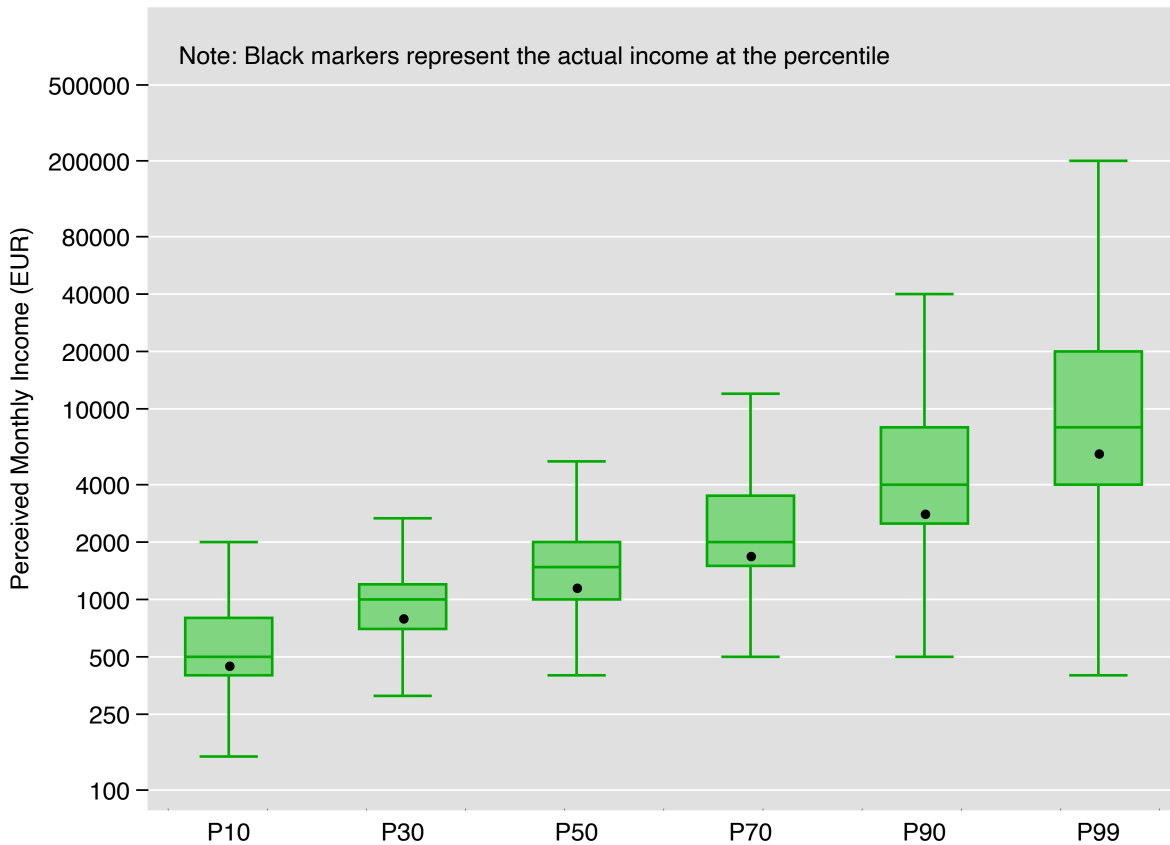


Figure 4: Perceived income distributions among respondents

Notes: This figure shows a boxplot of the perceived income distribution among survey respondents. The figure excludes outliers. The y-axis in the figure is log-scaled. The median perceived monthly incomes for the percentiles 10, 30, 50, 70, 90, and 99 are (in euros) 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 2018, were 446, 790, 1144, 1678, 2795, and 5791, respectively. These values correspond to the black markers in the figure.

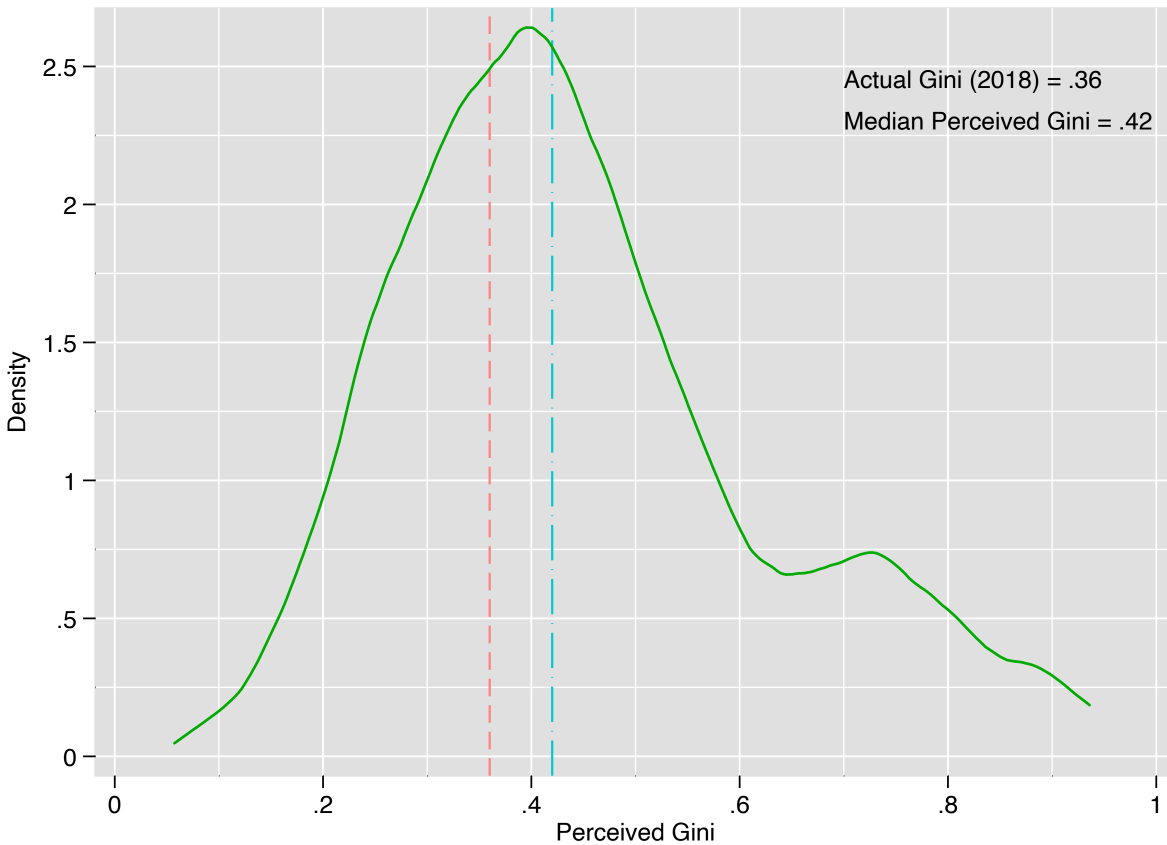


Figure 5: Perceived income inequality among respondents

Notes: This figure shows the distribution of *Perceived Gini* among survey respondents. Respondents' perceived income distribution at the national level was constructed by, first, asking them about the perceived incomes at the percentiles 10, 30, 50, 70, 90, and 99 (see Figure 3). With that, the entire perceived income distribution is computed applying linear interpolation (the first percentile is assigned an income of 0). *Perceived Income Gini* is the Gini index of that perceived income distribution. The mean value is 0.45. *Perceived Gini* in the percentiles 10, 25, 50, 75, and 90 is 0.24, 0.32, 0.42 (highlighted by the blue-dashed line), 0.54, and 0.73, respectively. According to the *Encuesta de Condiciones de Vida* (INE, 2018), the actual pre-tax Income Gini in Spain was approximately 0.36 (highlighted by the red-dashed line).

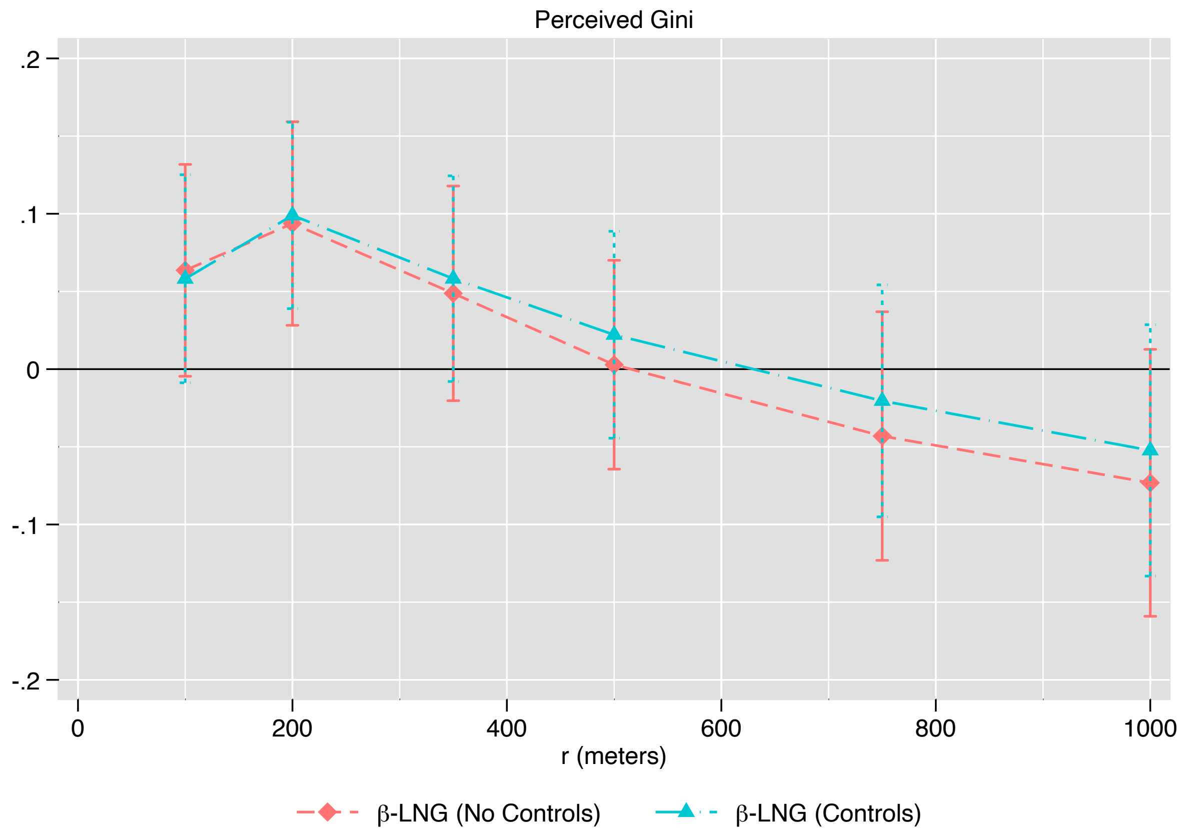


Figure 6: Local inequality (LNG) and inequality perceptions

Notes: This figure 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 2.5. 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. Vertical bars show 95% confidence intervals. 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. Heteroskedasticty-robust standard errors are clustered at the city-neighborhood level.

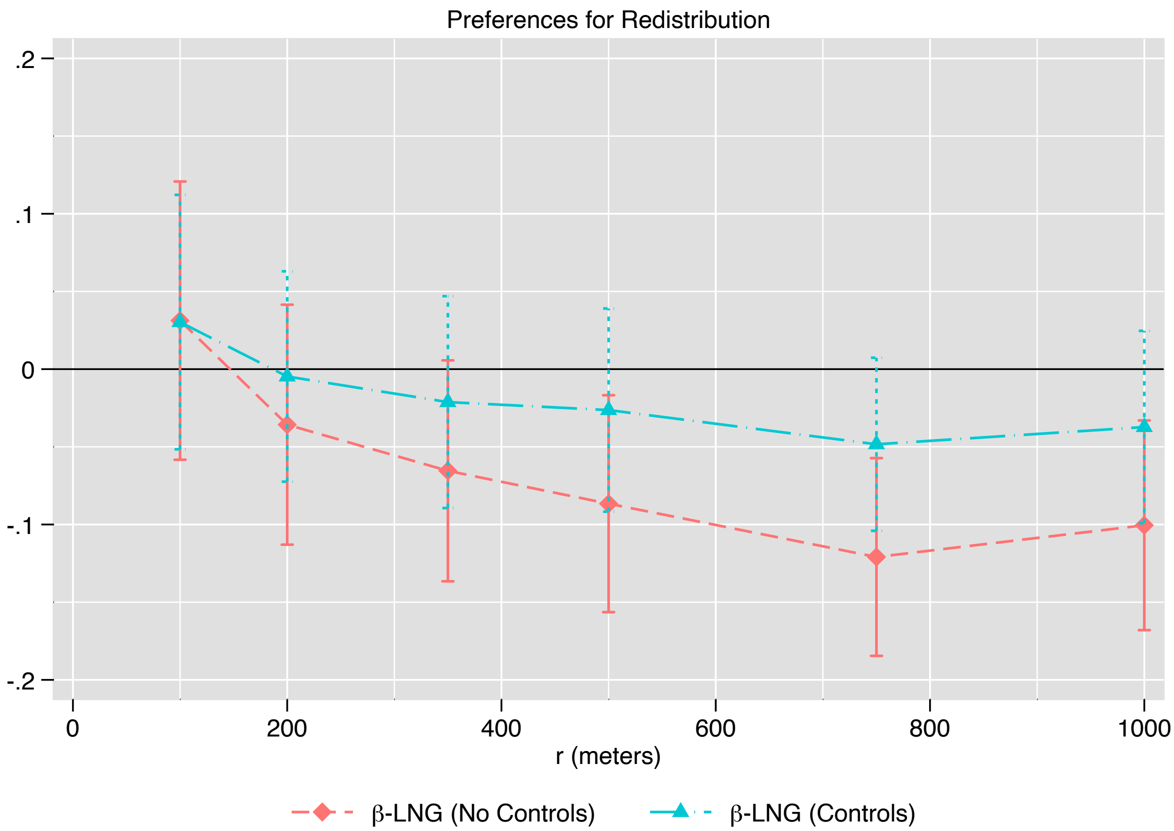


Figure 7: Local inequality (LNG) and preferences for redistribution

Notes: This figure explores the relationship between local inequality and preferences for redistribution. All continuous variables are standardized. Perceived inequality is measured with *Preferences for Redistribution* 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 2.5. 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. Vertical bars show 95% confidence intervals. 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. Heteroskedasticty-robust standard errors are clustered at the city-neighborhood level.

(a) Year 2012

(b) Year 2015

Figure 8: Example of an “apartment building shock”

Notes: This figure illustrates an example of a new apartment building shock. In 2012, the Local Neighborhood Gini (LNG) ($r = 100$) associated with the building shown in the top image was 0.02. In 2015, a new and modern building was constructed on a former parking lot, raising the LNG to 0.23. Building details: C/ Aiguablava 3, 08042 Barcelona (Cadastre code 1690916DF3819B). Images from Google Maps.

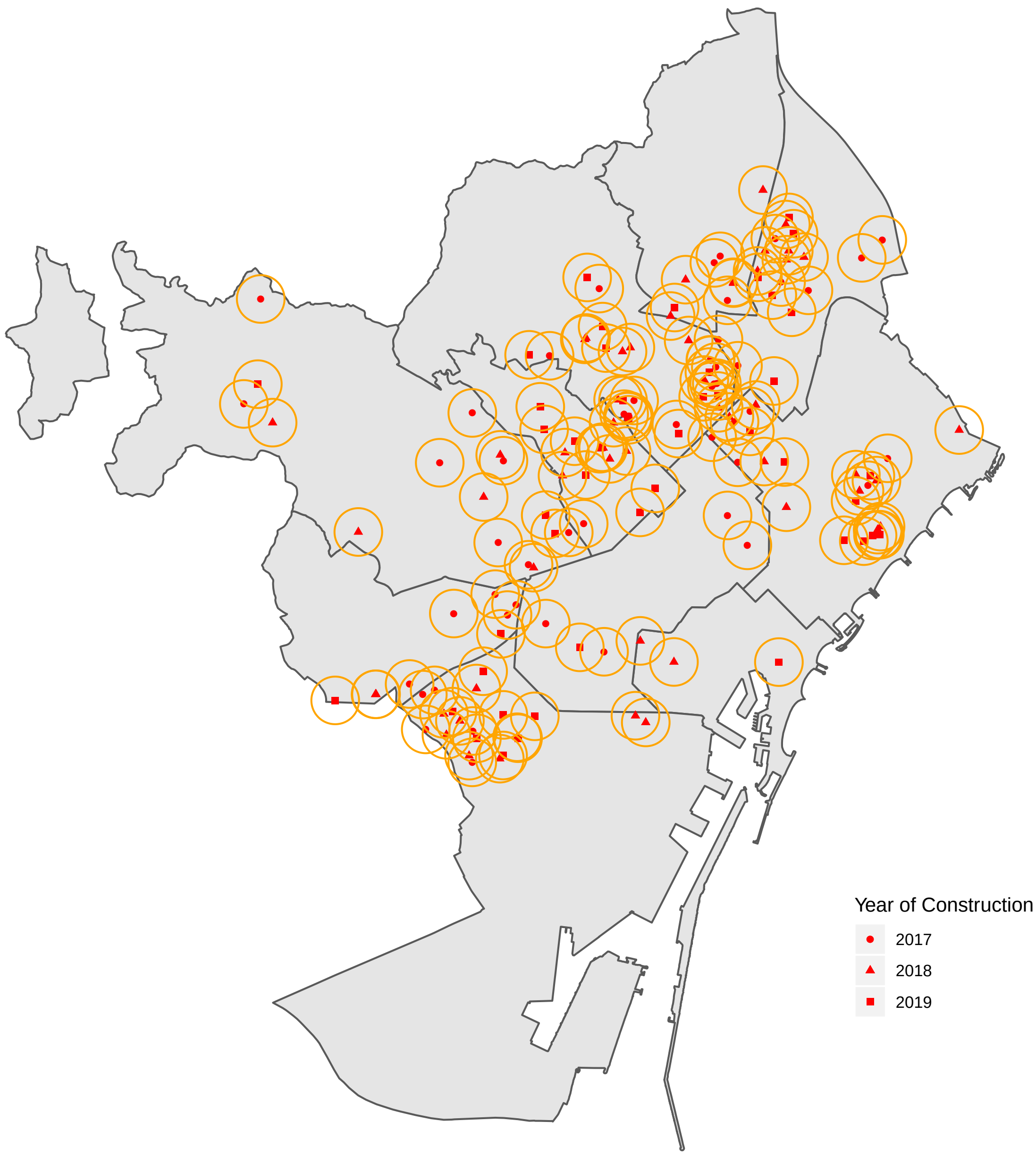


Figure 9: Visualization of the new apartment building identification strategy

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 either 2017, 2018, or 2019. Orange circumferences surrounding each marker represent 350 meters buffers. The baseline specification compares respondents who reside within one of these buffers (treated) with other respondents residing outside a buffer, within the same district. To alleviate sorting concerns, the sample is restricted to individuals already residing in the same dwelling in 2015.

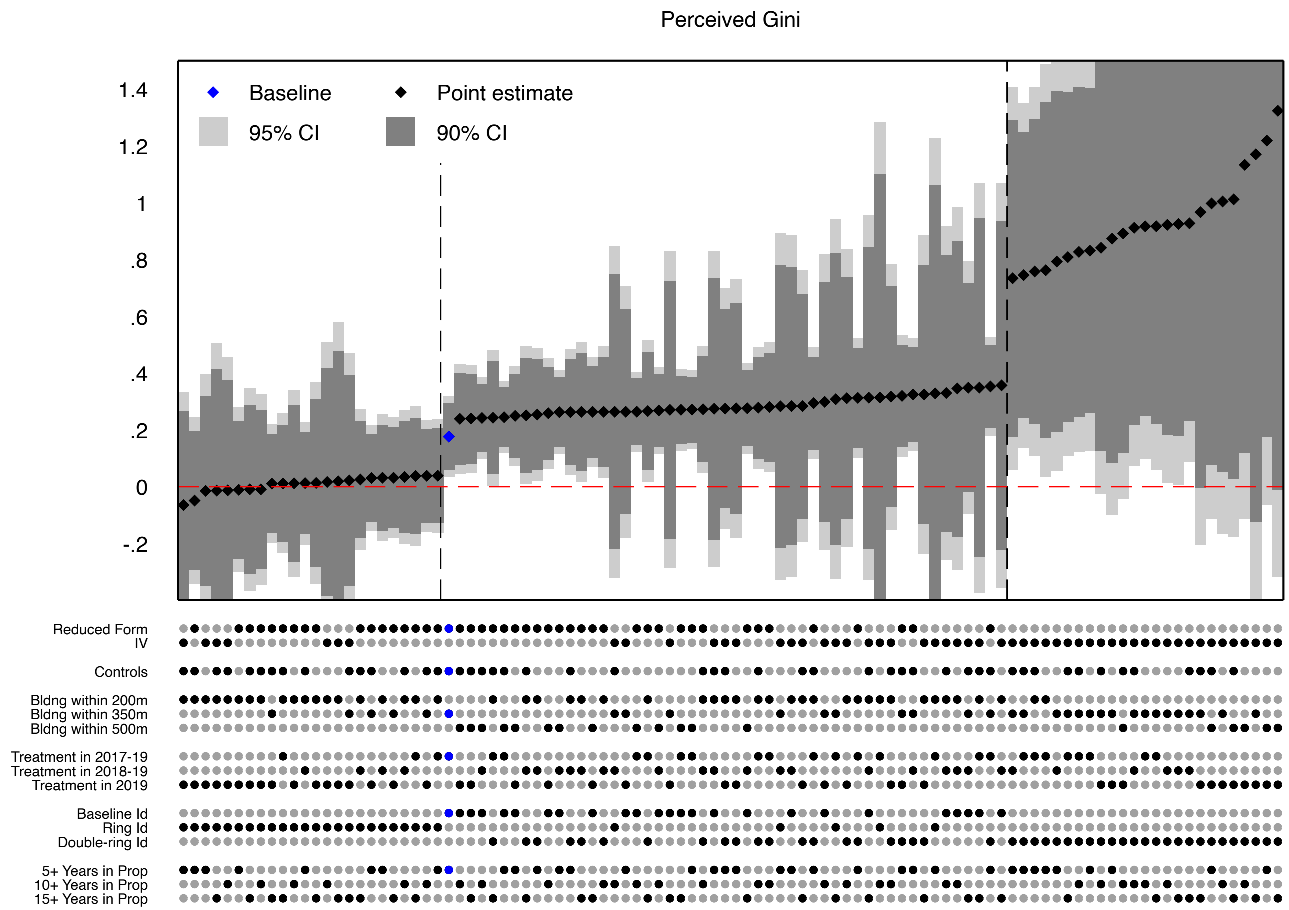


Figure 10: Specification curve: new building treatment and perceived inequality

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 A3 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 is -0.07 and the largest is 1.32. Coefficients are positive in 317 specifications and the mean value is 0.34. The baseline value is 0.18 (92nd smallest).

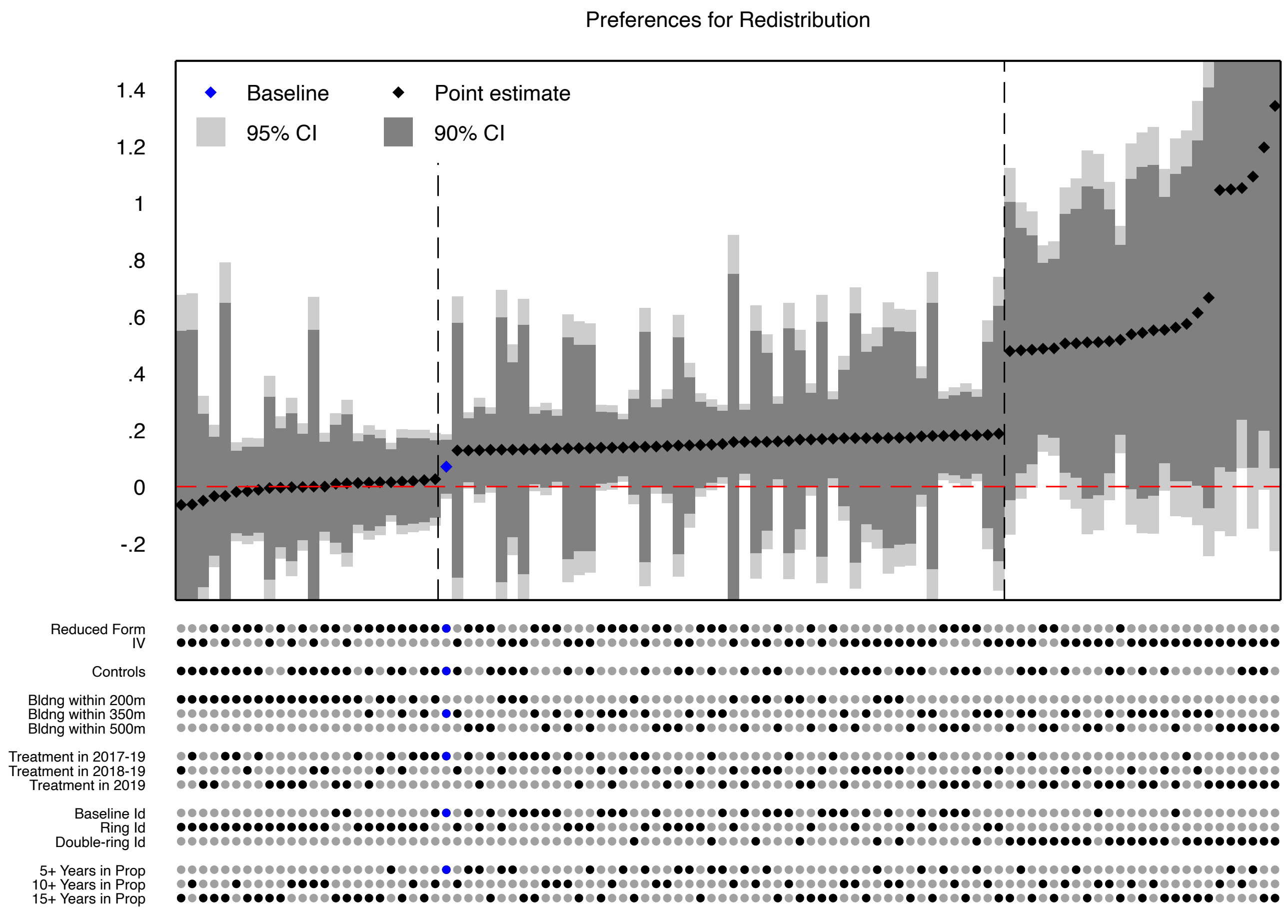


Figure 11: Specification curve: new building treatment and preferences for redistribution

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 A3 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 is -0.06 and the largest is 1.34. Coefficients are positive in 311 specifications and the mean value is 0.20. The baseline value is 0.07 (70th smallest).

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 12: 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 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 parenthesis.

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

	Perceived Gini		Preferences for Redistribution		
	(1)	(2)	(3)	(4)	(5)
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]
Perceived Gini					0.142***
					[0.028]
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
Controls	X	X	X	X	X
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. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 3: Local inequality (LNG) and inequality perceptions

	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*	0.058*	0.099***	0.058*	0.022	-0.020	-0.052
	[0.034]	[0.033]	[0.035]	[0.034]	[0.040]	[0.043]	[0.034]	[0.030]	[0.033]	[0.033]	[0.037]	[0.041]
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	0.008	0.007	0.008	0.009	0.059	0.062	0.058	0.057	0.057	0.058
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
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 2.5. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4: Local inequality (LNG) and preferences for redistribution

	Preferences for Redistribution											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LNG	0.032	-0.036	-0.065*	-0.087**	-0.121***	-0.101***	0.031	-0.004	-0.021	-0.026	-0.049*	-0.037
	[0.045]	[0.039]	[0.036]	[0.035]	[0.032]	[0.034]	[0.041]	[0.034]	[0.034]	[0.033]	[0.028]	[0.031]
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	0.015	0.017	0.015	0.193	0.192	0.192	0.192	0.193	0.193
N	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330	1330
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 2.5. Specifications across columns widen the spatial scope (r) of local neighborhoods, from 100 meters to 1 kilometer. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 5: New apartment building treatment and local inequality

	Δ LNG (Value)			Δ LNG (Space)		
	(1)	(2)	(3)	(4)	(5)	(6)
New Building Treatment (200m)	0.078 [0.109]			0.380*** [0.125]		
New Building Treatment (350m, baseline)		0.081 [0.149]			0.325*** [0.105]	
New Building Treatment (500m)			0.068 [0.226]			0.452*** [0.165]
r (meters)	200	350	500	200	350	500
Dep Var Mean (Non-std)	-0.123	-0.123	-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	0.071	0.112	0.202
N	1324	1324	1324	1324	1324	1324
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 construction (built in 2017-19). Sample size is not 1,330 as six individuals reside in dwellings constructed during 2016-19. All regressions include city-district fixed effects. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6: New apartment building treatment and perceived inequality

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.212***	0.176**	0.228***	0.200**	0.204**	0.173**	0.170	0.157	0.220***	0.165**
	[0.073]	[0.071]	[0.075]	[0.075]	[0.086]	[0.083]	[0.136]	[0.113]	[0.082]	[0.081]
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	0.060	0.019	0.056	0.018	0.049	0.036	0.131	0.021	0.054
N	937	937	704	704	586	586	301	301	636	636
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 construction (built 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. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: New apartment building treatment and preferences for redistribution

	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Building Treatment	0.113*	0.070	0.114*	0.080	0.138*	0.091	0.040	0.078	0.151*	0.066
	[0.058]	[0.057]	[0.068]	[0.071]	[0.074]	[0.073]	[0.105]	[0.102]	[0.077]	[0.075]
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	0.168	0.027	0.174	0.029	0.145	0.018	0.160	0.023	0.185
N	937	937	704	704	586	586	301	301	636	636
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 construction (built 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 in the same dwelling since at least 2010 or 2005. Columns 7-10 further restrict the sample to include only either renters or homeowners. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 8: 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	0.222***	0.171**	0.190**	0.142**	0.127*	0.081	0.111	0.067	0.098	0.055	-0.002	-0.033
	[0.072]	[0.066]	[0.072]	[0.069]	[0.071]	[0.066]	[0.072]	[0.066]	[0.068]	[0.062]	[0.069]	[0.066]
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	0.098	0.022	0.091	0.018	0.089	0.019	0.093	0.017	0.095	0.010	0.085
N	937	937	937	937	937	937	937	937	937	937	937	937
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 construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 9: Information treatment, perceived inequality, and preferences for redistribution

	Perceived Gini		Pref Redistribution	
	(1)	(2)	(3)	(4)
Neighborhood Info Treatment	0.064 [0.052]	0.068 [0.056]	0.064 [0.046]	0.069 [0.044]
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	0.049	0.001	0.186
N	1237	1237	1237	1237
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. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 10: 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)
Neighborhood Info Treatment	0.121**	0.120**	0.107*	0.101*	0.080	0.070	0.101*	0.089*	0.124**	0.111**	0.070	0.059
	[0.055]	[0.057]	[0.055]	[0.052]	[0.052]	[0.048]	[0.055]	[0.050]	[0.053]	[0.048]	[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	0.079	0.003	0.080	0.002	0.082	0.003	0.086	0.004	0.093	0.001	0.092
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
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 12). 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. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 11: 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)
Neighborhood Info Treatment	0.063	0.067	0.044	0.051	0.064	0.069	-0.060	-0.067
	[0.052]	[0.056]	[0.059]	[0.066]	[0.046]	[0.044]	[0.061]	[0.059]
Poor District	-0.111*	-0.058	-0.127*	-0.072	0.024	0.026	-0.081	-0.088
	[0.065]	[0.066]	[0.071]	[0.073]	[0.050]	[0.042]	[0.065]	[0.060]
Neighborhood Info Treatment × Poor District			0.033	0.028			0.221**	0.240***
			[0.099]	[0.105]			[0.085]	[0.082]
Sum of Treatment Effects			0.077	0.080			0.160***	0.173***
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	0.050	0.004	0.050	0.001	0.186	0.004	0.190
N	1237	1237	1237	1237	1237	1237	1237	1237
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 12). 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. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

A Additional figures

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.

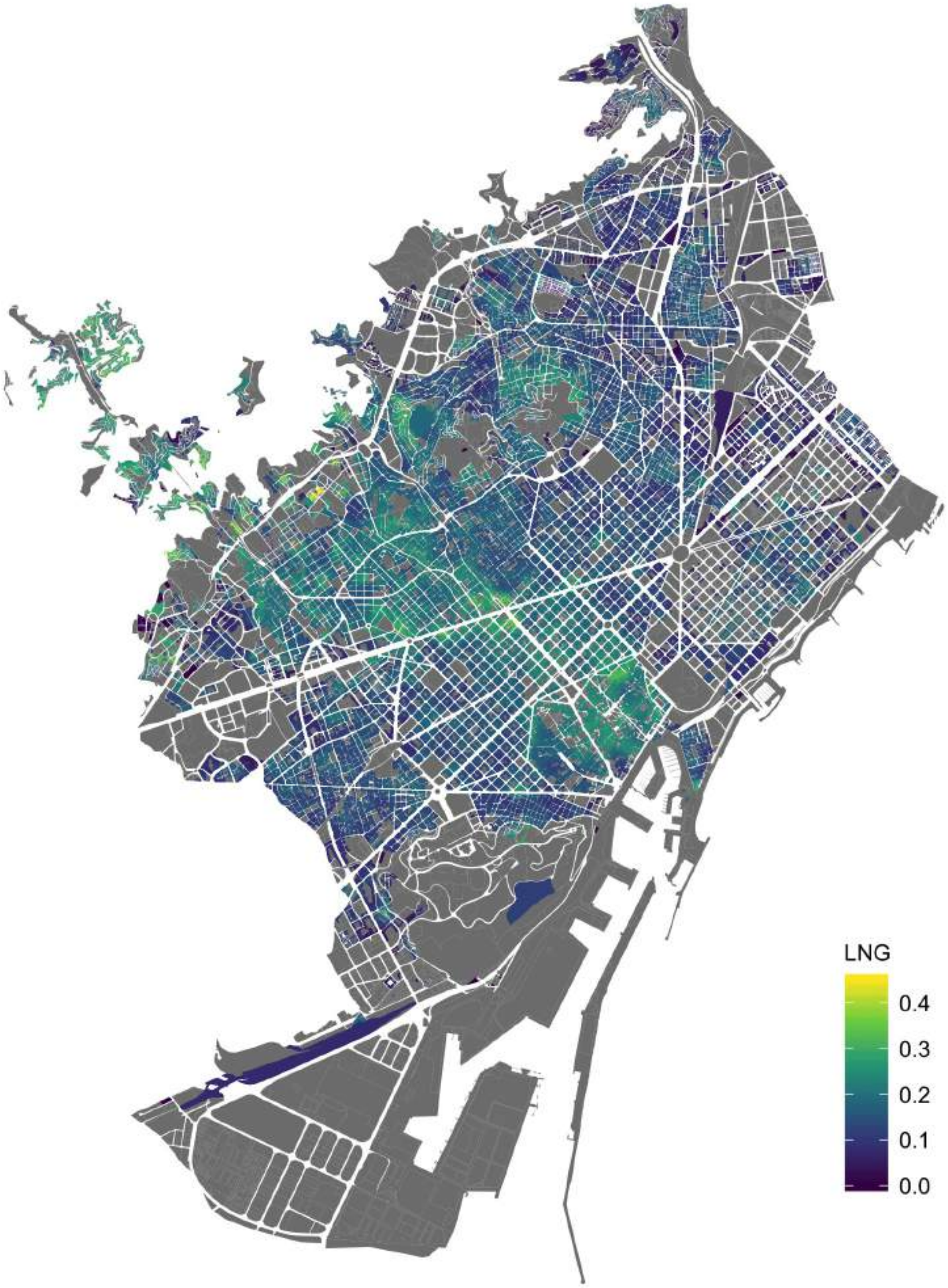
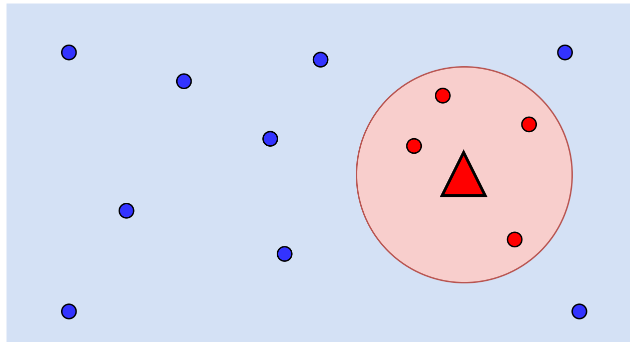
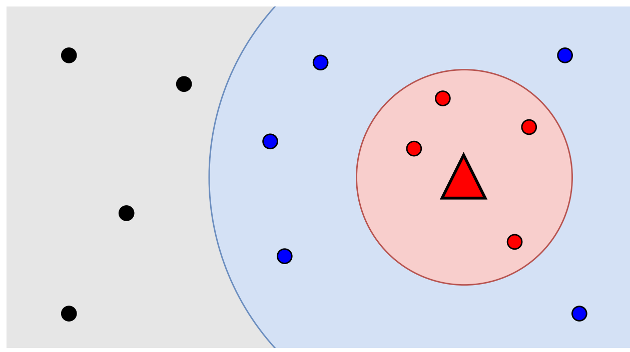


Figure A2: The Local Neighborhood Gini (LNG) in Barcelona ($r = 100$)

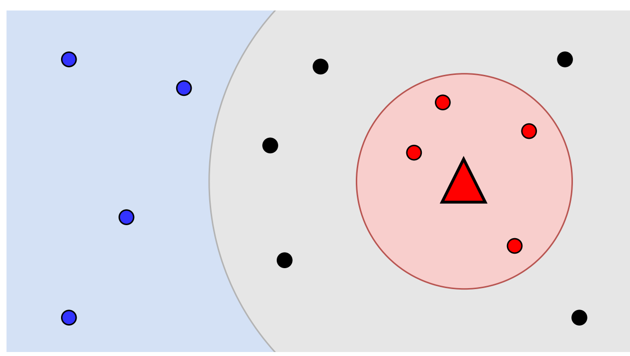
Notes: This figure shows the Local Neighborhood Gini (LNG) (dwelling value) in Barcelona ($r = 100$ meters). Lighter-color polygons correspond to plots (apartment buildings) with more unequal local neighborhoods. Darker polygons correspond to apartment buildings with more homogeneous local neighborhoods.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



(a) Baseline identification



(b) Ring identification



(c) Double-ring identification

Figure A3: 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.

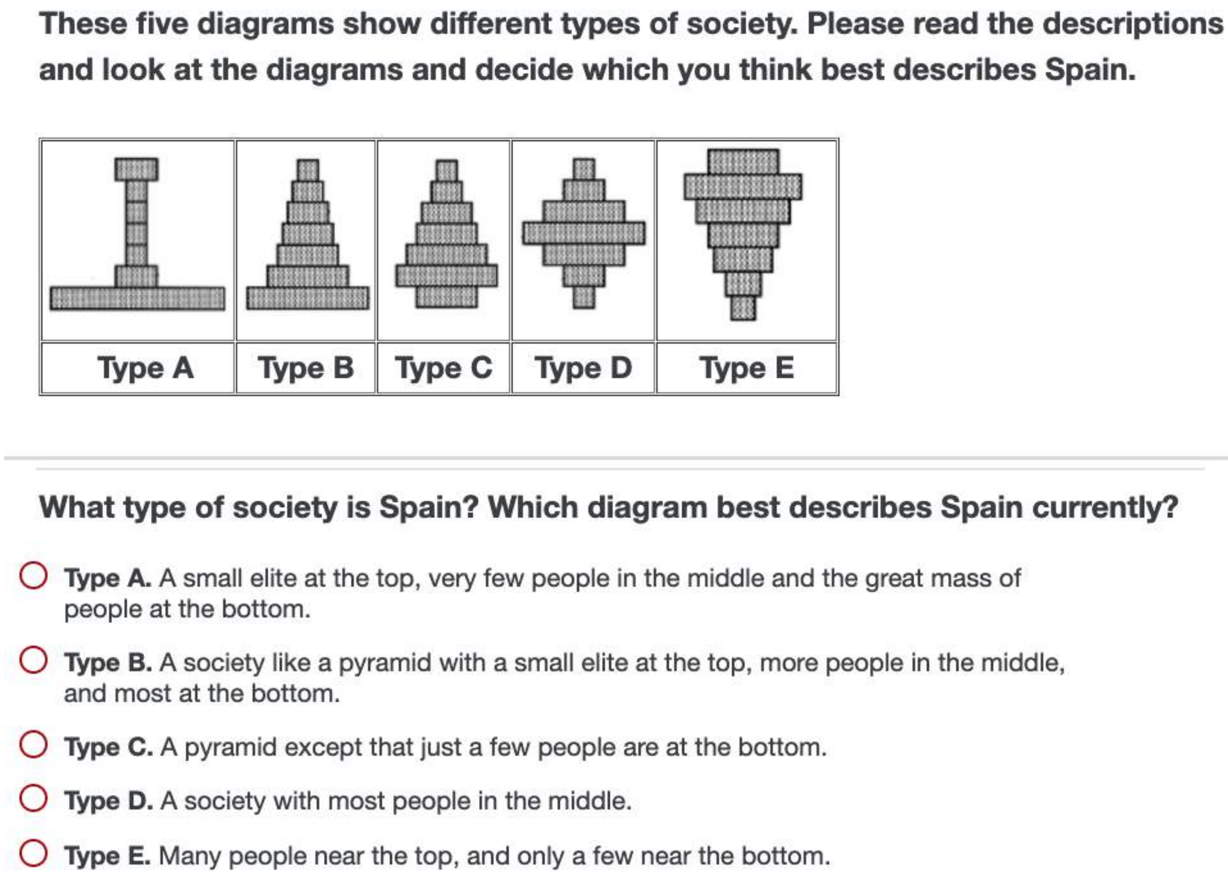


Figure A4: Screenshot of the alternative question eliciting inequality perceptions, borrowed from the ISSP (2009)

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.

B Additional tables

Table B1: 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 2.4 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.

Table B2: Sample distribution across the (10) districts and (73) neighborhoods of Barcelona, in comparison to the actual population

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

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 B3: 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B4: 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]
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]
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]
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]
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]
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]
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 2.5. 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B5: Covariate balance across treatment and control samples

	Panel A. New building treatment			**Panel B. Information treatment**		
	Treated	Control	Difference	Treated	Control	Difference
Female	0.441	0.448	-0.007	0.468	0.464	0.004
	(0.022)	(0.024)		(0.021)	(0.020)	
Age	49.321	49.864	-0.544	45.792	45.734	0.058
	(0.597)	(0.683)		(0.592)	(0.565)	
Married	0.525	0.545	-0.020	0.464	0.421	0.043
	(0.022)	(0.025)		(0.021)	(0.019)	
Foreign Born	0.071	0.099	-0.029	0.109	0.144	-0.035
	(0.011)	(0.015)		(0.013)	(0.014)	
University	0.601	0.550	0.052	0.633	0.641	-0.007
	(0.021)	(0.025)		(0.020)	(0.019)	
Renter	0.323	0.320	0.003	0.444	0.447	-0.003
	(0.020)	(0.023)		(0.021)	(0.020)	
Unemployed	0.092	0.092	-0.000	0.099	0.109	-0.010
	(0.013)	(0.014)		(0.012)	(0.012)	
HH Income (1000s EUR)	47.490	45.588	1.902	46.519	46.213	0.306
	(1.560)	(2.149)		(1.652)	(1.474)	
HH Size	2.721	2.772	-0.051	2.672	2.637	0.035
	(0.052)	(0.054)		(0.046)	(0.046)	
Religious	0.313	0.339	-0.026	0.283	0.303	-0.019
	(0.020)	(0.023)		(0.019)	(0.018)	
Left-wing	0.710	0.668	0.042	0.700	0.714	-0.015
	(0.020)	(0.023)		(0.019)	(0.018)	
N	524	413		586	651	

Notes: This table shows the covariate balance across treatment and control groups for the new apartment building treatment (in Panel A) and the within-survey information treatment (in Panel B). In Panel A, 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 in Panel A is restricted to individuals who have resided in the same dwelling since at least 2015. In Panel B, an individual is considered as treated if he or she was exposed to the question illustrated in Figure 12. The sample in Panel B 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. Covariates include age, household income, household size, and indicators for female, foreign, university, marital status, religiosity, left-wing Ideology, rental status, and employment status. Standard errors in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B6: New building treatment and perceived inequality (alternative identification strategies)

	Perceived Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline identification						
New Building Treatment	0.154	0.135	0.212***	0.176**	0.269***	0.243***
	[0.096]	[0.094]	[0.074]	[0.072]	[0.071]	[0.064]
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	0.012	0.058	0.018	0.061	0.020	0.065
N	937	937	937	937	937	937
Panel B. Ring identification						
New Building Treatment	0.068	0.038	0.128	0.094	0.214***	0.199***
	[0.101]	[0.100]	[0.079]	[0.080]	[0.064]	[0.060]
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	0.071	0.011	0.058	0.013	0.059
N	690	690	811	811	889	889
Panel C. Double-ring identification						
New Building Treatment	0.312***	0.294***	0.413***	0.355***	0.518***	0.419**
	[0.106]	[0.098]	[0.094]	[0.088]	[0.179]	[0.174]
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	0.092	0.034	0.088	0.026	0.079
N	522	522	650	650	738	738
Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table tests the robustness of the baseline results from Table 6 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. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B7: 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	0.079	0.045	0.113*	0.070	0.127*	0.092
	[0.069]	[0.062]	[0.058]	[0.057]	[0.068]	[0.057]
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	0.011	0.167	0.012	0.168	0.012	0.168
N	937	937	937	937	937	937
Panel B. Ring identification						
New Building Treatment	0.050	0.015	0.076	0.040	0.089	0.052
	[0.080]	[0.069]	[0.068]	[0.066]	[0.079]	[0.068]
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	0.157	0.011	0.165	0.013	0.175
N	690	690	811	811	889	889
Panel C. Double-ring identification						
New Building Treatment	0.101	0.079	0.190**	0.148*	0.311	0.290
	[0.083]	[0.075]	[0.084]	[0.080]	[0.197]	[0.212]
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	0.166	0.012	0.160	0.010	0.153
N	522	522	650	650	738	738
Controls		X		X		X
District FE	X	X	X	X	X	X

Notes: This table tests the robustness of the baseline results from Table 7 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. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B8: 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	0.135	0.135	0.176**	0.176**	0.243***	0.243***
	[0.094]	[0.094]	[0.072]	[0.072]	[0.064]	[0.064]
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	0.058	0.058	0.061	0.061	0.065	0.065
N	937	937	937	937	937	937
Panel B. Two-year window						
New Building Treatment in 2018-19	0.094	0.106	0.084	0.141*	0.137*	0.236***
	[0.095]	[0.102]	[0.069]	[0.077]	[0.069]	[0.069]
Dep Var Mean (Non-std)	0.441	0.438	0.441	0.436	0.441	0.437
Dep Var SD (Non-std)	0.176	0.173	0.176	0.171	0.176	0.173
R2	0.055	0.053	0.055	0.055	0.057	0.069
N	937	863	937	827	937	849
Panel C. One-year window						
New Building Treatment in 2019	-0.018	0.039	0.001	0.113	0.095	0.223***
	[0.136]	[0.138]	[0.078]	[0.090]	[0.072]	[0.084]
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	0.441	0.435	0.441	0.431	0.441	0.434
Dep Var SD (Non-std)	0.176	0.172	0.176	0.169	0.176	0.169
R2	0.053	0.048	0.053	0.050	0.055	0.061
N	937	779	937	675	937	666
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 6 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). 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B9: 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	0.045	0.045	0.070	0.070	0.092	0.092
	[0.062]	[0.062]	[0.057]	[0.057]	[0.057]	[0.057]
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	0.167	0.167	0.168	0.168	0.168	0.168
N	937	937	937	937	937	937
Panel B. Two-year window						
New Building Treatment in 2018-19	0.072	0.061	0.097	0.092	0.072	0.099*
	[0.073]	[0.072]	[0.058]	[0.056]	[0.055]	[0.057]
Dep Var Mean (Non-std)	6.487	6.494	6.487	6.520	6.487	6.496
Dep Var SD (Non-std)	2.311	2.318	2.311	2.299	2.311	2.333
R2	0.166	0.167	0.167	0.170	0.166	0.165
N	937	863	937	827	937	849
Panel C. One-year window						
New Building Treatment in 2019	0.023	0.047	0.070	0.102	0.124**	0.156**
	[0.102]	[0.096]	[0.065]	[0.065]	[0.060]	[0.067]
Inner Ring	200	200	350	350	500	500
Dep Var Mean (Non-std)	6.487	6.462	6.487	6.489	6.487	6.512
Dep Var SD (Non-std)	2.311	2.306	2.311	2.286	2.311	2.310
R2	0.166	0.175	0.167	0.165	0.169	0.174
N	937	779	937	675	937	666
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 7 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). 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B10: Local inequality (LNG) and perceived inequality — IV Results

	Perceived Gini							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ LNG (Value)	-0.025	-0.024	6.740	6.034				
	[0.045]	[0.042]	[32.531]	[30.043]				
Δ LNG (Space)					0.081**	0.080**	0.589**	0.498**
					[0.039]	[0.035]	[0.244]	[0.226]
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			0.042	0.040			11.254	11.947
R2	0.007	0.055			0.013	0.060		
N	935	935	935	935	935	935	935	935
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 construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B11: Local inequality (LNG) and preferences for redistribution — IV Results

	Preferences for Redistribution							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ LNG (Value)	-0.044	-0.041	3.414	2.288				
	[0.034]	[0.029]	[16.780]	[11.716]				
Δ LNG (Space)					0.043	0.039	0.298*	0.189
					[0.030]	[0.027]	[0.177]	[0.161]
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			0.042	0.040			11.254	11.947
R2	0.010	0.166			0.011	0.167		
N	935	935	935	935	935	935	935	935
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 construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B12: New apartment building treatment and inequality perceptions (alternative measures)

	log Perceived 90/10 Income Ratio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New Building Treatment	0.216**	0.191	0.209*	0.187***	0.104	0.210**	0.202***	0.189*	0.196**
	[0.091]	[0.153]	[0.114]	[0.064]	[0.106]	[0.086]	[0.062]	[0.101]	[0.084]
Dep Var Mean (Non-std)	2.241	2.241	2.241	2.241	2.241	2.241	2.241	2.241	2.241
Dep Var SD (Non-std)	1.391	1.236	1.460	1.391	1.236	1.460	1.391	1.236	1.460
R2	0.040	0.098	0.043	0.039	0.095	0.044	0.039	0.098	0.041
N	937	301	636	937	301	636	937	301	636
	log Perceived 90/50 Income Ratio								
New Building Treatment	0.175*	0.163	0.149	0.167**	0.132	0.152*	0.221***	0.208**	0.200***
	[0.092]	[0.170]	[0.114]	[0.069]	[0.100]	[0.078]	[0.064]	[0.101]	[0.074]
Dep Var Mean (Non-std)	1.121	1.189	1.089	1.121	1.189	1.089	1.121	1.189	1.089
Dep Var SD (Non-std)	0.780	0.867	0.734	0.780	0.867	0.734	0.780	0.867	0.734
R2	0.041	0.098	0.040	0.041	0.098	0.041	0.044	0.101	0.043
N	937	301	636	937	301	636	937	301	636
	Perceived Gini (Pyramid)								
New Building Treatment	0.114	0.305**	0.055	0.027	0.155	-0.004	0.044	0.036	0.095
	[0.071]	[0.137]	[0.085]	[0.059]	[0.126]	[0.078]	[0.082]	[0.138]	[0.093]
Inner Ring	200	200	200	350	350	350	500	500	500
Dep Var Mean (Non-std)	0.327	0.331	0.325	0.327	0.331	0.325	0.327	0.331	0.325
Dep Var SD (Non-std)	0.075	0.078	0.074	0.075	0.078	0.074	0.075	0.078	0.074
R2	0.080	0.152	0.068	0.078	0.142	0.068	0.078	0.138	0.069
N	937	301	636	937	301	636	937	301	636
Controls	X	X	X	X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X
Sample	Full	Renters	Owners	Full	Renters	Owners	Full	Renters	Owners

Notes: This table tests the robustness of the baseline results from Table 6 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 A4), 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 1-3), 350 (Columns 4-6), or 500 (Columns 7-9) meters of a new construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 2015. Columns 2, 5, and 8 further restrict the sample to renters. Columns 3, 6, and 9 further restrict the sample to homeowners. 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B13: New building treatment and preferences for redistribution (alternative measures)

Panel A. Survey Data									
	Preferences for Redistribution (No Trade-off)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New Building Treatment	0.109*	0.306***	0.014	0.021	0.051	-0.006	0.132*	0.150	0.099
	[0.059]	[0.102]	[0.090]	[0.064]	[0.126]	[0.077]	[0.070]	[0.158]	[0.088]
Dep Var Mean (Non-std)	5.994	6.140	5.925	5.994	6.140	5.925	5.994	6.140	5.925
Dep Var SD (Non-std)	2.552	2.606	2.524	2.552	2.606	2.524	2.552	2.606	2.524
R2	0.086	0.156	0.103	0.084	0.142	0.103	0.087	0.145	0.105
N	937	301	636	937	301	636	937	301	636
	Voted a Left-wing Party								
New Building Treatment	0.020	0.003	0.037	0.037	0.019	0.061**	0.045*	0.074	0.047
	[0.030]	[0.062]	[0.029]	[0.027]	[0.050]	[0.028]	[0.025]	[0.055]	[0.028]
Dep Var Mean (Non-std)	0.725	0.769	0.705	0.725	0.769	0.705	0.725	0.769	0.705
Dep Var SD (Non-std)	0.447	0.422	0.456	0.447	0.422	0.456	0.447	0.422	0.456
R2	0.360	0.384	0.378	0.361	0.384	0.381	0.362	0.388	0.379
N	828	251	577	828	251	577	828	251	577
Sample	Full	Renters	Owners	Full	Renters	Owners	Full	Renters	Owners
Panel B. Aggregate Electoral Data									
	Left-wing Parties Vote Share								
New Building Treatment	0.035	0.004	0.059*	0.062***	0.032	0.090**	0.058**	0.021	0.086**
	[0.022]	[0.029]	[0.032]	[0.022]	[0.031]	[0.035]	[0.027]	[0.047]	[0.034]
Inner Ring	200	200	200	350	350	350	500	500	500
Dep Var Mean (Non-std)	0.639	0.640	0.639	0.639	0.640	0.639	0.639	0.640	0.639
Dep Var SD (Non-std)	0.091	0.079	0.101	0.091	0.079	0.101	0.091	0.079	0.101
R2	0.931	0.917	0.943	0.931	0.918	0.944	0.931	0.917	0.944
N	1058	534	524	1058	534	524	1058	534	524
Controls	X	X	X	X	X	X	X	X	X
District FE	X	X	X	X	X	X	X	X	X
Share Rentals (Rel to Median)	All	Above	Below	All	Above	Below	All	Above	Below

Notes: This table investigates the effects of the new building treatment on demand for redistribution. All continuous variables are standardized. The dependent variables in Panel A are *Preferences for Redistribution (No Trade-off)*, a question measuring demand for redistribution in a scale from 0 to 10 and borrowed from Fehr et al. (2019), and *Voted a Left-wing Party*, an indicator taking the value of 1 if the individual voted for a left-wing party in the November 2019 national election. The dependent variable in Panel B is *Left-wing Parties Parties Vote Share*, capturing the vote share obtained by left-wing parties in the November 2019 national election (measured at the census tract). *New Building Treatment* is an indicator taking the value of 1 if the individual (in Panel A) or the centroid of the census tract (in Panel B) is located within 200 (Columns 1-3), 350 (Columns 4-6), or 500 (Columns 7-9) meters of a new construction built in 2017-19. Sample in Panel A is restricted to individuals residing in the same dwelling from at least 2015. Columns 2, 5, and 8 further restrict the sample to renters (Panel A) or tracts with a share of rentals above the median in the city (Panel B). Columns 3, 6, and 9 further restrict the sample to homeowners (Panel A) or to tracts with a share of rentals below the median in the city (Panel B). Controls in Panel A include Age, log Household Income, and indicators for Female, Foreign, University, Marital Status, Religiosity, Left-wing Ideology, Rental Status, and Employment Status. Controls in Panel B include Mean Age, log Median Household Income (2017), share Female, share Foreign, share of University Graduates (2011), share Married (2011), vote share obtained by the left-wing parties in the 2015 national election (as a proxy for left-wing ideology), 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table B14: 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)
Neighborhood Info Treatment	0.119**	0.085	0.100*	0.078	0.068	0.059	0.087*	0.082	0.110**	0.100	0.059	0.038
	[0.057]	[0.076]	[0.052]	[0.078]	[0.049]	[0.080]	[0.050]	[0.089]	[0.049]	[0.086]	[0.043]	[0.070]
Poor District	-0.097*	-0.125*	-0.086	-0.105	-0.130**	-0.138	-0.113*	-0.117	-0.107	-0.116	-0.012	-0.029
	[0.058]	[0.074]	[0.058]	[0.080]	[0.065]	[0.096]	[0.066]	[0.102]	[0.064]	[0.103]	[0.054]	[0.082]
Neighborhood Info Treatment × Poor District		0.059		0.039		0.016		0.010		0.019		0.036
		[0.108]		[0.105]		[0.101]		[0.107]		[0.104]		[0.091]
Sum of Treatment Effects		0.144*		0.117*		0.075		0.092		0.118**		0.074
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	0.081	0.081	0.081	0.081	0.086	0.086	0.089	0.089	0.096	0.096	0.092	0.093
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
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 12). 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. 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Heterogeneity

C1 Overview

In this appendix, 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 origin as the most relevant dimensions.

C2 Perceived inequality and preferences for redistribution

I start by investigating the accuracy of perceived income distributions in Figure C1. In that figure, and in those that follow, 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 3, 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 a better job predicting incomes in those 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 income throughout the distribution. Another noticeable contrast is on ideology. Relative to right-wing individuals, left-wingers perceive lower income at the bottom and higher incomes at the top.

Figure C2 shows the cumulative distributions of *Perceived Gini* along the same dimensions and sample splits. Consistent with results previously described, individuals with a college degree and, especially, left-wingers appear to perceive more inequality. The CDF for this latter group first-order stochastically dominates that of right-wingers, a result consistent with Chambers et al. (2014). Apart from these two categories, non-religious individuals also appear to perceive more inequality, but contrasts are not as stark as those on ideology. Visually, there do not appear to be 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. Among all them, ideology arises once more as the most relevant. 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. Apart from ideology, non-religious individuals, renters, and college graduates also appear to be more in favor of redistribution generally. Nonetheless, the contrast is not as stark.

C3 Local inequality

Figures C4 and C5 replicate Equation 1 splitting the sample across the same dimensions. In general, there is no strong evidence of heterogeneity along any specific covariate. However, left-wing, high-income, and religious individuals perceive slightly more inequality when exposed to more unequal local environments in narrow neighborhoods. Regarding distributional preferences, females, renters, and high-income individuals appear to react to more local inequality by demanding more redistribution when neighborhoods are narrowly defined.

C4 New apartment building treatment

Tables C1 and C2 explore the heterogeneous effects of the new apartment building treatment. The treatment appears to be especially effective among left-wingers, that significantly perceive more inequality after being exposed to a new construction. However, the effect on demand for redistribution for this subgroup is not statistically different from zero. A similar pattern arises among low-educated and low-income individuals. Apart from that, younger individuals and natives do also significantly perceive more inequality after being treated. As before, in both cases, the effect on demand for redistribution is positive but not statistically significant. Finally, unmarried individuals also appear to perceive more inequality after being treated, but the effects on redistribution preferences are going in opposite directions.

C5 Information treatment

Finally, Tables C3 and C4 explore heterogeneity in the information treatment. Results suggest that effects are slightly larger among non-college-educated, low-income, and individuals born in Spain. These groups perceive higher inequality and demand more redistribution after the treatment exposure.

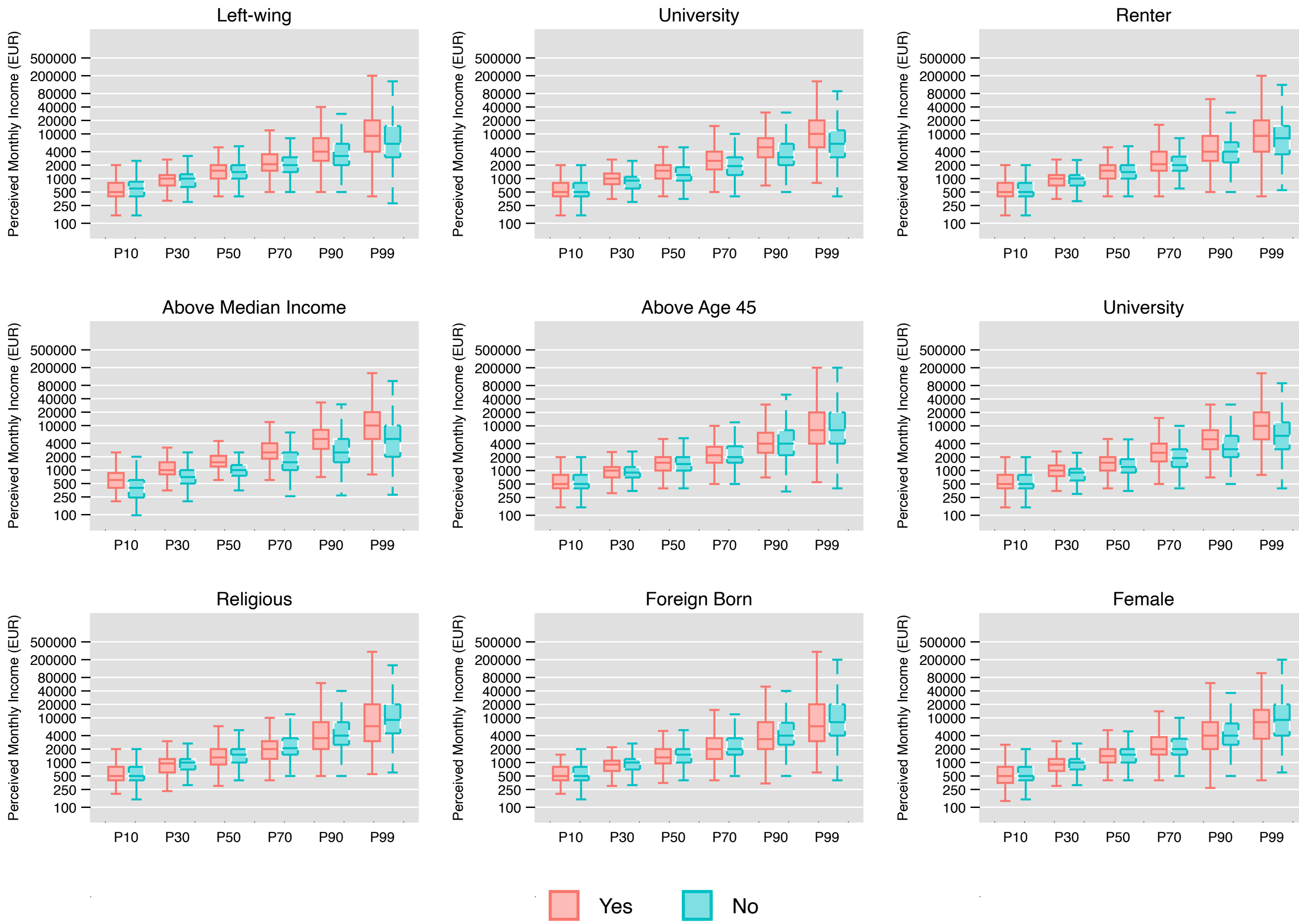


Figure C1: Perceived income distributions among respondents (heterogeneity)

Notes: This figure explores heterogeneity in the perceived 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 in the figure 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 for these percentiles, in the year 2018, were 446, 790, 1144, 1678, 2795, and 5791, respectively.

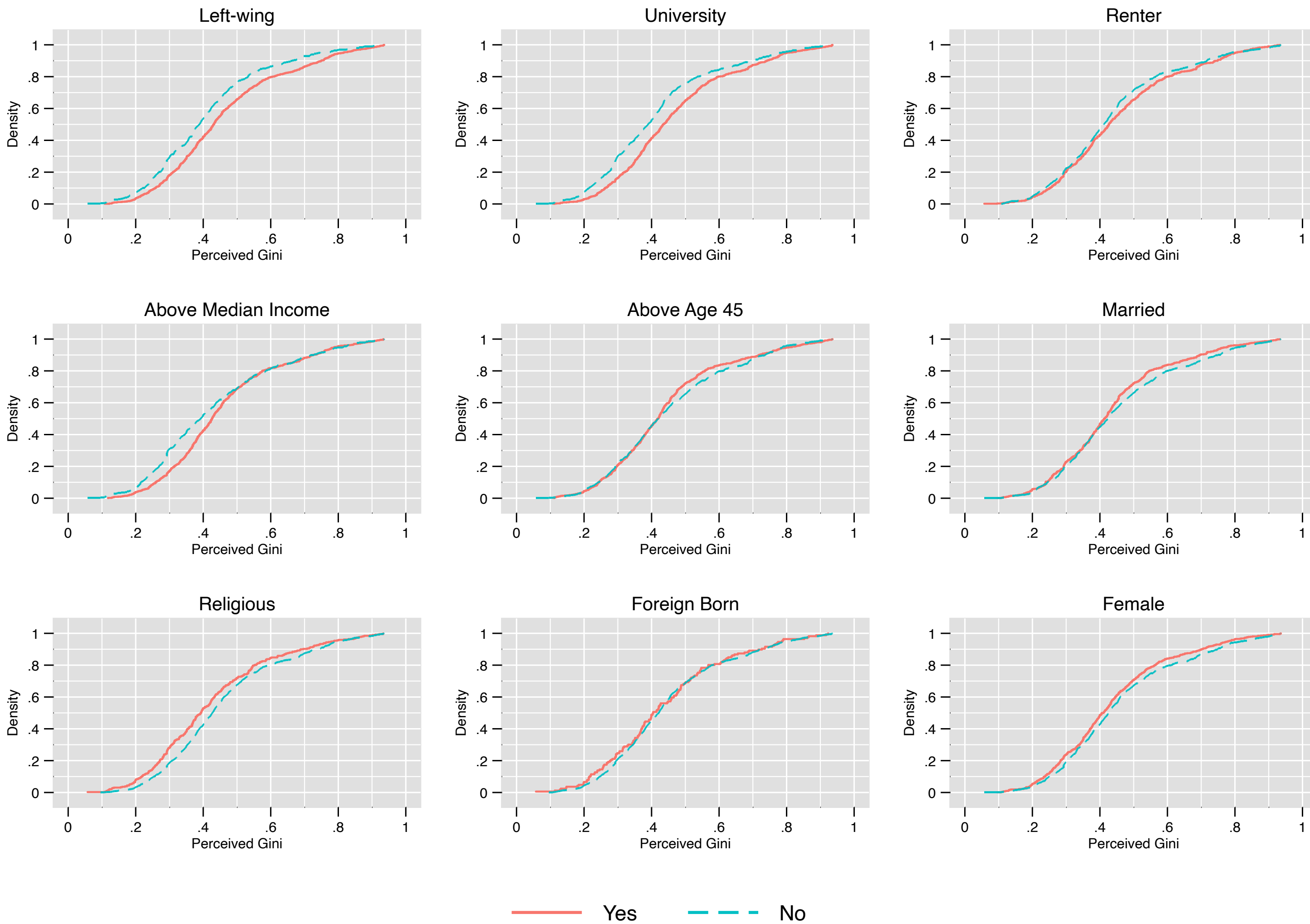


Figure C2: Cumulative distributions of *Perceived Gini* (heterogeneity)

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 income distribution. Each figure plots the spearate CDFs resulting from splitting the sample along a binary covariate. 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).

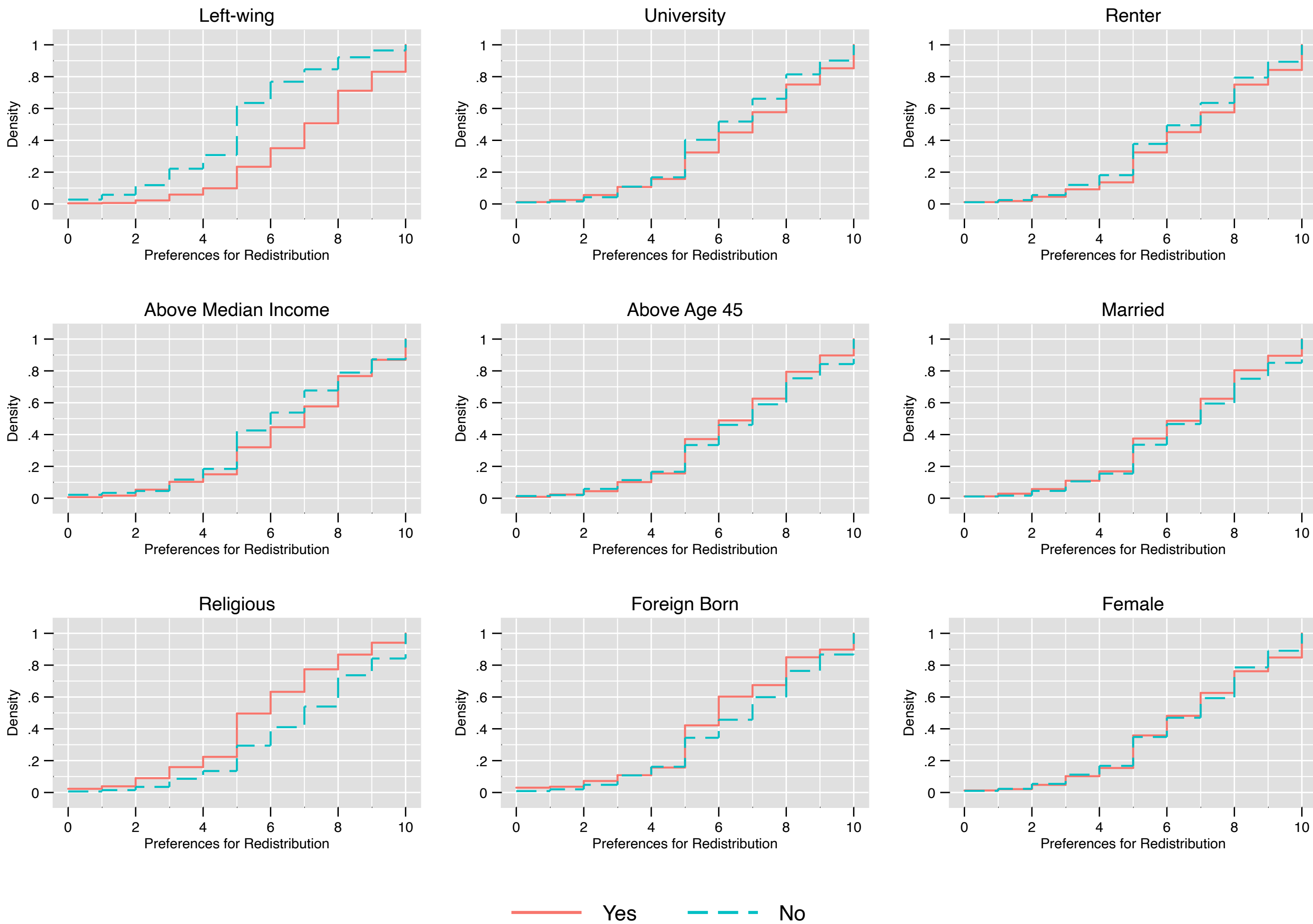


Figure C3: Cumulative distributions of *Preferences for Redistribution* (heterogeneity)

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 in a scale from 0 to 10, with 10 representing the highest demand for redistribution. Each figure plots the spearate CDFs resulting from splitting the sample along a binary covariate. 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).

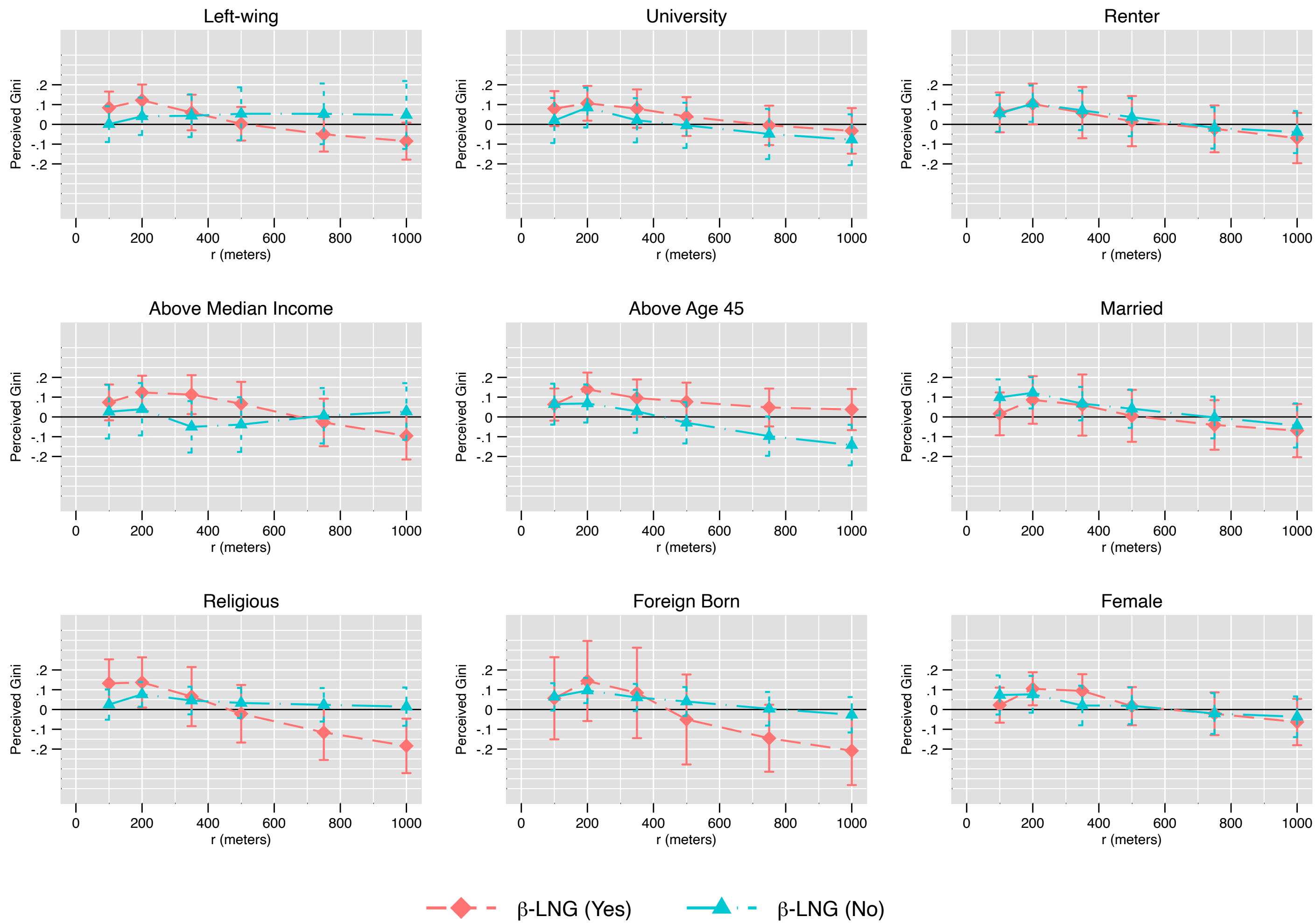


Figure C4: Local inequality (LNG) and perceived inequality (heterogeneity)

Notes: This figure explores the relationship between local and perceived inequality. All continuous variables are standardized. *Perceived Gini* is the Gini index of the respondent's perceived income distribution. 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 2.5. Each coefficient in the plot is an OLS estimate of β in Equation 1, with the spatial scope of neighborhoods (characterized by r) varying over the x-axis. Each figure plots the spearate coefficients resulting from splitting the sample along a binary covariate. 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). 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. Heteroskedasticity-robust standard errors are clustered at the city-neighborhood level.

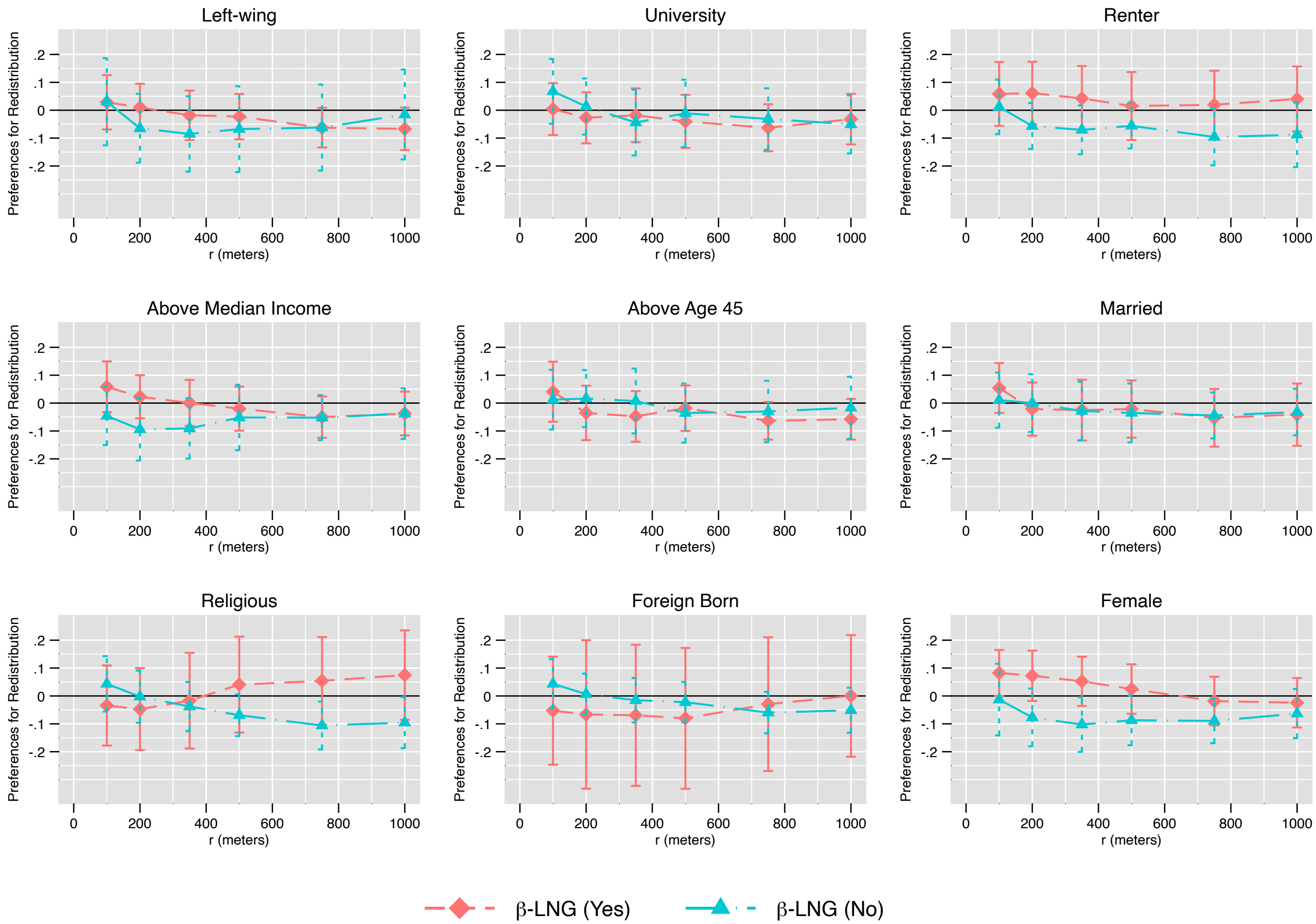


Figure C5: Local inequality (LNG) and preferences for redistribution (heterogeneity)

Notes: This figure explores 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 2.5. Each coefficient in the plot is an OLS estimate of β in Equation 1, with the spatial scope of neighborhoods (characterized by r) varying over the x-axis. Each figure plots the spearate coefficients resulting from splitting the sample along a binary covariate. Vertical bars show 95% confidence intervals. 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). 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. Heteroskedasticity-robust standard errors are clustered at the city-neighborhood level.

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	0.176**	-0.024	0.119	0.171**	0.214*	0.382***	0.306***	0.172**	0.215***	0.134
	[0.071]	[0.123]	[0.112]	[0.080]	[0.121]	[0.119]	[0.098]	[0.071]	[0.074]	[0.106]
New Building Treatment × Left-wing		0.297**								
		[0.134]								
New Building Treatment × University			0.105							
			[0.150]							
New Building Treatment × Renter				0.026						
				[0.131]						
New Building Treatment × Above Med Inc					-0.052					
					[0.136]					
New Building Treatment × Above Age 45						-0.308**				
						[0.138]				
New Building Treatment × Married							-0.233*			
							[0.121]			
New Building Treatment × Religious								0.022		
								[0.127]		
New Building Treatment × Foreign Born									-0.419*	
									[0.247]	
New Building Treatment × Female										0.103
										[0.136]
Sum of Treatment Effects		0.273***	0.224**	0.197	0.162*	0.073	0.073	0.194	-0.204	0.237**
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	0.060	0.063	0.059	0.058	0.058	0.063	0.061	0.058	0.061	0.059
N	937	937	937	937	937	937	937	937	937	937
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 construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 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). 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. Robust standard errors clustered at the city-neighborhood level in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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	0.070 [0.057]	0.072 [0.103]	0.119 [0.083]	0.069 [0.072]	0.046 [0.087]	0.087 [0.108]	0.025 [0.086]	0.014 [0.075]	0.083 [0.058]	0.083 [0.075]
New Building Treatment × Left-wing		0.005 [0.133]								
New Building Treatment × University			-0.078 [0.119]							
New Building Treatment × Renter				0.020 [0.125]						
New Building Treatment × Above Med Inc					0.044 [0.111]					
New Building Treatment × Above Age 45						-0.017 [0.138]				
New Building Treatment × Married							0.093 [0.113]			
New Building Treatment × Religious								0.185 [0.142]		
New Building Treatment × Foreign Born									-0.088 [0.192]	
New Building Treatment × Female										-0.017 [0.117]
Sum of Treatment Effects		0.077	0.042	0.089	0.090	0.069	0.118	0.199*	-0.005	0.066
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	0.168	0.165	0.165	0.165	0.165	0.165	0.165	0.167	0.165	0.165
N	937	937	937	937	937	937	937	937	937	937
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 construction (built in 2017-19). The sample is restricted to individuals who have resided in the same dwelling since at least 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). Controls include Age, log Household Income, 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C3: Neighborhood information treatment and perceived inequality (heterogeneity)

	Perceived Gini									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Neighborhood Info Treatment	0.068	0.013	0.147	0.042	0.163*	0.041	0.107	0.049	0.062	0.071
	[0.056]	[0.087]	[0.089]	[0.068]	[0.095]	[0.092]	[0.087]	[0.072]	[0.062]	[0.074]
Neighborhood Info Treatment × Left-wing		0.074								
		[0.107]								
Neighborhood Info Treatment × University			-0.128							
			[0.127]							
Neighborhood Info Treatment × Renter				0.054						
				[0.100]						
Neighborhood Info Treatment × Above Med Inc					-0.140					
					[0.104]					
Neighborhood Info Treatment × Above Age 45						0.049				
						[0.122]				
Neighborhood Info Treatment × Married							-0.093			
							[0.118]			
Neighborhood Info Treatment × Religious								0.058		
								[0.128]		
Neighborhood Info Treatment × Foreign Born									0.032	
									[0.179]	
Neighborhood Info Treatment × Female										-0.011
										[0.106]
Sum of Treatment Effects		0.087	0.019	0.096	0.023	0.089	0.014	0.107	0.093	0.060
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	0.049	0.046	0.047	0.046	0.047	0.046	0.046	0.046	0.046	0.046
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
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). 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C4: Neighborhood information treatment and preferences for redistribution (heterogeneity)

	Preferences for Redistribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Neighborhood Info Treatment	0.069 [0.044]	0.019 [0.109]	0.152** [0.075]	0.037 [0.065]	0.140 [0.096]	-0.032 [0.060]	0.033 [0.062]	0.060 [0.049]	0.091* [0.046]	0.017 [0.073]
Neighborhood Info Treatment × Left-wing		0.063 [0.131]								
Neighborhood Info Treatment × University			-0.139 [0.096]							
Neighborhood Info Treatment × Renter				0.058 [0.107]						
Neighborhood Info Treatment × Above Med Inc					-0.111 [0.111]					
Neighborhood Info Treatment × Above Age 45						0.185* [0.094]				
Neighborhood Info Treatment × Married							0.067 [0.105]			
Neighborhood Info Treatment × Religious								0.010 [0.105]		
Neighborhood Info Treatment × Foreign Born									-0.228 [0.153]	
Neighborhood Info Treatment × Female										0.100 [0.104]
Sum of Treatment Effects		0.081	0.013	0.095	0.029	0.153**	0.101	0.070	-0.137	0.117*
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	0.186	0.182	0.183	0.182	0.183	0.184	0.183	0.182	0.184	0.183
N	1237	1237	1237	1237	1237	1237	1237	1237	1237	1237
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). 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

D Survey description

D1 Overview

The online survey was conducted by Netquest from May 28, 2020, to June 9, 2020. As mentioned in Section 3.1, the company was instructed 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. However, 99 of them had to be discarded as they could not be matched to a valid address.[64] Also, 15 additional observations were dropped due to inconsistencies between responses and Netquest's records (e.g., in the gender or age of the participant). The final sample includes 1,330 participants.

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

D2 Address matching

The address matching process to the Cadastre data was carried combining fuzzy string matching in R with manual matching. Each address was first cleaned both in the Cadastre and survey data by removing special characters and non-content words (e.g., "de", "la", "d'en"). Once strings were cleaned, the algorithm would find the best match between a survey and an official address using the Levenshtein distance as a criterion. Matching was done using the universe of addresses within a ZIP Code, retrieved from the Cadastre. Approximately 75% of the addresses were exactly matched (distance of 0). Among those, a small fraction was randomly checked manually to assess the quality of the match. All addresses that did not exactly match were manually checked. A relevant fraction of those (about 10-15%) was finally assigned to the closest matched address. On many occasions, the reason for not obtaining an exact match was a typo. The rest (about 10%) had to be manually matched. 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").

D3 Attrition

Survey attrition was 24%. It is slightly larger than what Netquest originally anticipated (20%), but in accordance with figures from other studies.[65] As in Kuziemko et al. (2015), attrition was not random. In particular, female, older, and lower socioeconomic status individuals were significantly less likely to complete the survey.

D4 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

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

[65] 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, and only a few more were added. Most of the changes made involved adapting the survey to the COVID-19 pandemic. Spain was amidst a strict lockdown since mid-March and until June 20th, completely overlapping with the survey. Therefore, it was essential to adapt the questions and their wording to the new circumstances. Changes into the survey were carefully planned and in consultation with experts in survey design, including two staff from the University of Southern California Center for Economic and Social Research. The list below contains a summary of the main guidelines followed in the adaptation process:

- Minimize to the extent possible the use of the word COVID in order 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).

D5 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 12]
   (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/riches ...% 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: