Measuring local, salient economic inequality in the UK

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Abstract: *Neighbourhood-level economic inequality is thought to have important implications for social, political, and economic attitudes and behaviours. However, due to a lack of available data, to date it has been impossible to investigate how inequality varies across neighbourhoods in the UK. In this paper, I develop a novel measure of within-neighbourhood inequality in the UK by exploiting data on housing values for over 26.6 million addresses – nearly the universe of residential properties in the UK. Across two surveys, I demonstrate that housing value inequality is perceptually-salient – what people see around them in terms of housing discrepancies is associated with their beliefs about inequality. This new measure of local, salient inequality represents a powerful tool with which to investigate both the anatomy of local inequality in the UK, as well as its attitudinal and behavioural consequences.*

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1 Introduction

Recent years have seen burgeoning academic interest in understanding the consequences of economic inequality for human attitudes and behaviour. Scholars interested in this question tend to treat inequality as a *macro* phenomenon, however. As a result, the geographical resolution at which inequality is typically measured is the country or region-level, with far fewer studies looking at lower spatial levels (Cavanaugh & Breau, 2018). Local inequality – i.e. economic inequality within neighbourhoods – has been largely neglected as a focus of measurement and study, although there are good reasons to think that it is important.

Seen from the vantage point of the *neigbourhood effects* literature (Ellen & Turner, 1997; Galster, 2012; Wilson, 2012) and *relative deprivation theory* (Runciman, 1966; Smith et al., 2012), a macro-lens is not well suited for investigating the consequences of inequality for individuals' attitudes and behaviour. This is because the contexts within which people spend much of their time, the neighbourhoods and environments where we observe and accumulate knowledge, make acquaintances and form friendships, act and react, and thus the appropriate geographical resolution at which inequality should be measured in order to shed light on many individual-level impacts, is far below the macro-level. In other words, experiences of economic discrepancies happen at the micro-level, and therefore understanding how inequality affects important economic, political and social attitudes and behaviours requires corresponding measurement.

Granularity is not the only important feature of a measure of inequality; its salience -- i.e. the degree to which people perceive it -- is also relevant. A growing body of work demonstrates that it is perceptions of inequality, rather than actual levels, that drive behaviour (Cruces et al., 2013; Hauser & Norton, 2017; A. Kuhn, 2019). A salient measure of inequality may therefore be more relevant for understanding the consequences of inequality than a purely objective one.

In this paper, I exploit a large volume of housing value information to develop a measure of local economic inequality in the UK and examine the extent to which it is associated with people's perceptions of local inequality. The main contributions are twofold:

First, I measure economic inequality in the UK at a resolution that has been hitherto impossible, providing a contemporary picture of inequality in neighbourhoods across the UK, as well as changes over the twenty year period from 1999 to 2019.

There is only a limited understanding of how economic inequality varies at the local level in the UK. The UK does not collect income information from its residents as part of the census, thereby making it difficult to reliably measure economic inequality at a fine geographical level. This constraint has led researchers of inequality in the UK to limit their focus on the regional level (Carrascal-Incera et al., 2020; Corrado & Corrado, 2011; Gough, 2018; Hills et al., 2010), with the exception of N. Lee et al. (2016), who estimate wage inequality for 60 British cities.

The housing value information comes from Zoopla, an online property price aggregator in the UK that provides house price estimates, and the Land Registry of England and Wales, a ledger of realised residential property sales. Combined, I have real and estimated housing value data for over 26.6 million UK addresses. This is roughly 91% of the total number of UK addresses delivered to by the Royal Mail (around 29 million).[2]

A descriptive analysis reveals a couple of striking facts: First, there is substantial variation in neighbourhood inequality in the UK. Urban areas in the UK tend to exhibit extremes – neighbourhoods of extremely high and extremely low levels of inequality, oftentimes side-by-side. Second, inequality has declined on average over the last couple decades in England and Wales. However, there is substantial variation in experiences of inequality change at the local level, with many areas seeing large increases, notably Central London, Greater Manchester and the North East.

Second, I examine whether housing value inequality affects perceptions of economic inequality. This exercise allows me to validate the use of housing data for estimating inequality as well as providing the first empirical evidence of a relationship between features of the built environment and perceptions of inequality.

There is good reason to suspect that housing value inequality, as opposed to measures of inequality based on income or wealth, is salient. Recent theoretical work suggests housing,

[2] According to figures provided by Royal Mail here: https://www.royalmail.com/personal/marketplace/make-the-most-of-mail.

among other physical attributes, constitutes an important aspect of the local environment which individuals might use to form judgments about inequality (Phillips et al., 2020).

I test whether housing value inequality affects perceptions of economic inequality using two surveys. First, Wave 3 of the British Election Study (BES; 2015), which includes a module on perceptions of local neighbourhood income inequality, and second, a representative sample of UK participants (age, gender, income, and region) that I recruited via Qualtrics (N = 1029). I find that housing value inequality is indeed associated with perceptions, even after controlling for a number of important factor, for example political orientation and educational attainment. The second survey allows me to replicate findings from the first as well as include additional controls known to be important for inequality perceptions, in particular Social Dominance Orientation (Ho et al., 2015) and Personal Relative Deprivation (Callan et al., 2011), which are missing from the BES. Altogether the findings suggest that inequality based on housing values is salient – what people see around them, housing in particular, affects what they believe about economic inequality.

In what follows, I first provide the theoretical and conceptual basis for focusing on local economic inequality and, relatedly, the importance of understanding what determines perceptions of inequality. Section 3 details the data on local inequality in the UK and provides a brief descriptive analysis, Section 4 explores the link between these measures and people's perceptions of inequality, and Section 5 concludes by discussing the paper's overall contributions, limitations, and potential uses of the data presented here in future research.

An interactive map to explore and download the data is available online: https://github.com/jhsuss/uk-local-inequality.

2 Background

This paper builds on existing literature that emphasises the importance of local, perceptually-salient economic inequality and helps motivate the use of housing values to estimate local inequality.

2.1 Why local inequality matters

Evidence from the 'neighbourhood effects' literature suggests that local contexts matter above and beyond individual characteristics. Neighbourhood features, in particular levels of affluence and disadvantage, have been shown to affect a range of individual outcomes, from voting behaviour (Johnston et al., 2004) and redistributive attitudes (Bailey et al., 2013; Bertrand et al., 2000), to mental (Aneshensel & Sucoff, 1996) and physical health (Block et al., 2004). Galster (2012) considers the causal mechanisms running from neighbourhoods to individual outcomes, suggesting an important role for social interactions, e.g. social networks, social contagion and comparison, and social observation and accumulation of knowledge about the world, among other potential pathways.[3]

While the neighbourhood effects literature predominately considers inter-neighbourhood inequality, within-neighbourhood inequality is also likely to affect individual behaviour through the social-interactive mechanisms defined by Galster (2012). This view is supported by social psychological theoretical work on relative deprivation (Runciman, 1966). Relative deprivation theory emphasises the importance of local comparisons and reference groups for individual emotional and behavioural outcomes (see Smith et al., 2012 for a systematic review). Feelings of deprivation translate into negative emotional responses, e.g. anger and frustration, and have been shown to affect inter-group relationships (Smith & Huo, 2014), economic behaviour (Kim et al., 2017), and political preferences (Brown-Iannuzzi et al., 2015). Nieuwenhuis et al. (2017) integrate the neighbourhood effects and relative deprivation literatures by examining how adolescent problem behaviour is affected by moving to a more affluent neighbourhood. The authors find that adolescent behaviour is negatively associated with neighbourhood affluence, contrary to expectations arising from neighbourhood channels, due to relative family income –

[3] See also Ellen & Turner (1997), who provide a conceptual framework for thinking about how neighbourhoods affect individuals and families, paying specific attention to potential heterogeneous effects across the life-course and by family type.

moving to a wealthier neighbourhood can make family income relatively worse in comparison, which can thereby trigger feelings of relative deprivation.

Relatedly, research on the 'relative income hypothesis' (Duesenberry, 1949) finds that what our neighbours earn has an influence our feelings and behaviour (Hagerty, 2000; P. Kuhn et al., 2011; Luttmer, 2005; Senik, 2009). For example, Luttmer (2005) finds that having relatively less income than the average in a local area reduces subjective wellbeing, and P. Kuhn et al. (2011) find that households are more likely to increase consumption when their neighbour wins the lottery.

While relative deprivation suggests local inequality has negative consequences for those that are relatively worse off, the implications of neighbourhood effects are more ambiguous. From a positive perspective, local inequality involves the mixing of rich and poor, which may help to foster cross-class friendships and reduce stereotypes and stigmatisation (Dorling, 2017), as well as improve provision of public goods (Galster, 2007). This perspective was operationalised through mixed housing policies in the UK and other European countries in recent years, which sought to engender 'social mixing' between rich and poor in local neighbourhoods as a means of alleviating poverty and disadvantage, albeit the evidence that these policies ultimately conferred benefits is limited (Arthurson, 2002; Bolt et al., 2010; Cheshire, 2007; Meen et al., 2005; Ostendorf et al., 2001).

Taken together, whether leading to 'good' or 'bad' outcomes, it is clear that local contexts matter, and the distribution of economic resources within local contexts especially so.

2.2 Measuring inequality using housing values

While the importance of local inequality is clear, much remains to be understood. This is especially true in the case of the UK, where there is simply a lack of information on local economic inequality. This is primarily due to data availability. Studies exploring local inequality are generally situated in the US, Canada, and other countries which gather census information on income or wealth (for example, Chetty & Hendren, 2018; Newman et al., 2015). The UK does not ask residents about their income or wealth as part of its decennial census, and therefore lacks granular information with which to measure local inequality (Hills et al., 2010; N. Lee et al., 2016). Existing surveys and administrative data are also not up to the task, given the low number of observations for the former, and the incomplete nature of the latter, e.g. many people do not file tax returns (M. Kuhn et al., 2020).

I rectify this using a large volume of residential housing values. As residential housing assets make up a large majority – approximately 60% – of overall UK household wealth[4], inequality based on housing values can best be thought of as a measure of wealth inequality (Causa et al., 2019; M. Kuhn et al., 2020). Indeed, there is a strong correlation between reported housing wealth and overall household wealth in the UK's Wealth and Assets Survey (r = 0.79). Housing values have been used as a proxy measure of accumulated wealth and both individual and neighbourhood socio-economic status in previous work examining their links to health and educational outcomes (Connolly et al., 2010; Leonard et al., 2016; Ware, 2019).[5]

A general concern with using housing values to measure local inequality is that the data does not allow us to distinguish between houses that are owned or rented, occupied or vacant. Housing value inequality therefore may not correspond with traditional objective inequality measures based on the actual wealth (or income) of the inhabitants of a local area. While in the next section I stress the importance of a perceptually-salient measure of inequality rather than one that is solely objective, I acknowledge that this is an empirical question that should be addressed, perhaps by correlating measures of inequality based on housing values with those that are based on income or wealth. Given that there are no granular measures of income or wealth inequality available for the UK, this is not currently possible. However, it can conceivably be done using data from other countries where estimates from the different sources are available.

While using property values to measure inequality would be considered novel from the point of view of contemporary inequality scholars, it is a conventional approach used by economic historians interested in understanding patterns of economic inequality far back in time. In the complete absence of census data, household surveys or other records, historians instead rely on archaeological remnants of ancient housing to provide inequality estimates (Alfani, 2021; Kohler

[4] Author's calculation from total UK household wealth (not including private pension wealth) from the ONS Wealth and Asset Survey Wave 6 statistical release: https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/totalwealthingreatbritain/april2016tomarch2018

[5] Note that, in contrast to urban economic theory (e.g., Fujita, 1989), which is concerned with explaining variation in prices across space, the measure constructed here is for the distribution of house prices *within* neighbourhoods rather than the distribution of average prices across neighbourhoods.

et al., 2017). Examining distribution of house sizes has been used to construct inequality measures for Britain stretching as far back as the Iron Age (Stephan, 2013), and information on property tax and rent values has been used to construct inequality measures for medieval and pre-industrial European societies Soltow & Van Zanden (1998).[6]

Thus, in the absence of sufficiently granular, detailed data on income or wealth in the UK, using housing values provides reasonable estimates of local economic inequality.

2.3 Salient inequality

Importantly, housing value inequality might also be perceptually-salient. A growing body of academic literature across disciplines stresses the importance of perceptions of inequality, finding that perceived economic inequality differs substantially from actual levels (Chambers et al., 2014; Gimpelson & Treisman, 2018; Hauser & Norton, 2017; Kiatpongsan & Norton, 2014; Norton & Ariely, 2011), and that perceptions of inequality shape attitudes and behaviour (Ansell & Cansunar, 2020), more so than actual levels in some domains, for example redistributive preferences (Bamfield & Horton, 2009; Bobzien, 2020; Choi, 2019; Cruces et al., 2013; A. Kuhn, 2019), and social mobility beliefs (Davidai, 2018). From this perspective, measuring local inequality using conventional sources (i.e. income) might not be suitably salient. Indeed, a body of work using US data finds conflicting results when looking at the relationship between local income inequality and perceptions of local inequality (Minkoff & Lyons, 2019; Newman et al., 2018).

Nascent empirical research emphasises the importance of salient forms of local inequality. For example, Sands (2017) and Sands & Kadt (2020) demonstrate that visible cues of inequality (poor individuals or expensive cars) in local areas affect support for redistributive policies. DeCelles & Norton (2016) find that air rage is more prevalent when coach passengers have to pass through first class compartments on airplanes. Moreover, experimental evidence spanning multiple disciplines – sociology, political science, economics, and the psychological sciences – shows that observable manifestations of inequality in small-scale settings affect individual attitudes and behaviour (Butler, 2016; Hauser et al., 2016; Kuziemko et al., 2014; Nishi et al.,

[6] Of course, given classical work by Alonso (2013) [1964] in urban economic theory, the size of houses and land lots is only one factor that determines economic value, and so the distribution of house sizes might be an imperfect proxy for estimating inequality.

2015; Payne et al., 2017; Trump, 2016). While these experimental studies are mainly conducted in artificial lab settings or online and do not therefore fully reflect how inequality is actually experienced day-to-day, they nevertheless point to the importance of salient, localised forms of inequality.

How are perceptions of inequality formed? This is an important and under-examined question. Recent theoretical work by Phillips et al. (2020) suggests three different types of informational cues are important: i) interpersonal comparisons; ii) media attention; and iii) physical attributes of the built environment – e.g. schools, public spaces, cars and houses. While empirical evidence exists to support the first two channels (see Dawtry et al., 2015; Diermeier et al., 2017), there has not yet been any empirical work (as far as I am aware) that examines whether physical attributes affect inequality perceptions.

The hypothesis that physical attributes of the built environment affects perceptions of inequality is compatible with the 'neighbourhood effects' literature discussed above and also makes sense from a behavioural science perspective. Rather than being rational agents with perfect information about inequality levels, and because we are social creatures that consider it impolite to ask our neighbours what they earn, we make judgments based on what we are able to observe in our immediate surroundings, e.g. the quality of the neighbouring houses, or the cars our neighbours drive and other visible consumption choices. I provide evidence on whether physical attributes affect inequality perceptions in this paper by focusing on housing value inequality.

3 Data

3.1 Housing value inequality

I exploit information on housing values to produce measures of local inequality in the UK. The data comes from two sources: 1) the online UK property aggregator Zoopla, and 2) the Land Registry of England and Wales. The former more allows for a more comprehensive assessment of contemporary inequality, while the latter allows for measuring changes in inequality over the last twenty years.

The data from Zoopla was gathered in September 2019 and provides point in time value estimates for over 22.9 million addresses in the UK. The estimates are based on the output of a valuation model which uses previous sale prices, property attributes, information on similar properties in the area, changes in market prices and other local-level information (e.g. distance to central areas, transport links).[7]

Data from the Land Registry consists of realised sale prices of residential housing in England and Wales beginning in 1995. After excluding transfers under a power of sale and repossession, transfers to non-private individuals, and buy-to-lets, there are just over 24 million transactions lodged with the Land Registry between 1995 and 2019. Other transactions, such as right-to-buy purchases, are not included in the dataset.[8]

I gather observations from the Land Registry into five year windows in order to increase the number of realised transactions per granular geographic area. Within each window, I remove repeated transactions for the same property in favour of the latest and adjust prices in line with inflation to the end of the window using the UK Office for National Statistics (ONS) House Price Index (HPI) broken down by Local Authority District and property type.[9] This results in estimates of inequality at every five year interval, from 1999 to 2019, with an average of roughly 4.8 million transactions per interval.

I take the Gini coefficient as the preferred measure of inequality. This can be calculated for a given area as the mean absolute difference between each pair of observations divided by two times the mean housing value, or formally:

$$G = \frac{1/n^2 \sum_{i,j} | y_i - y_j |}{2\overline{y}}$$

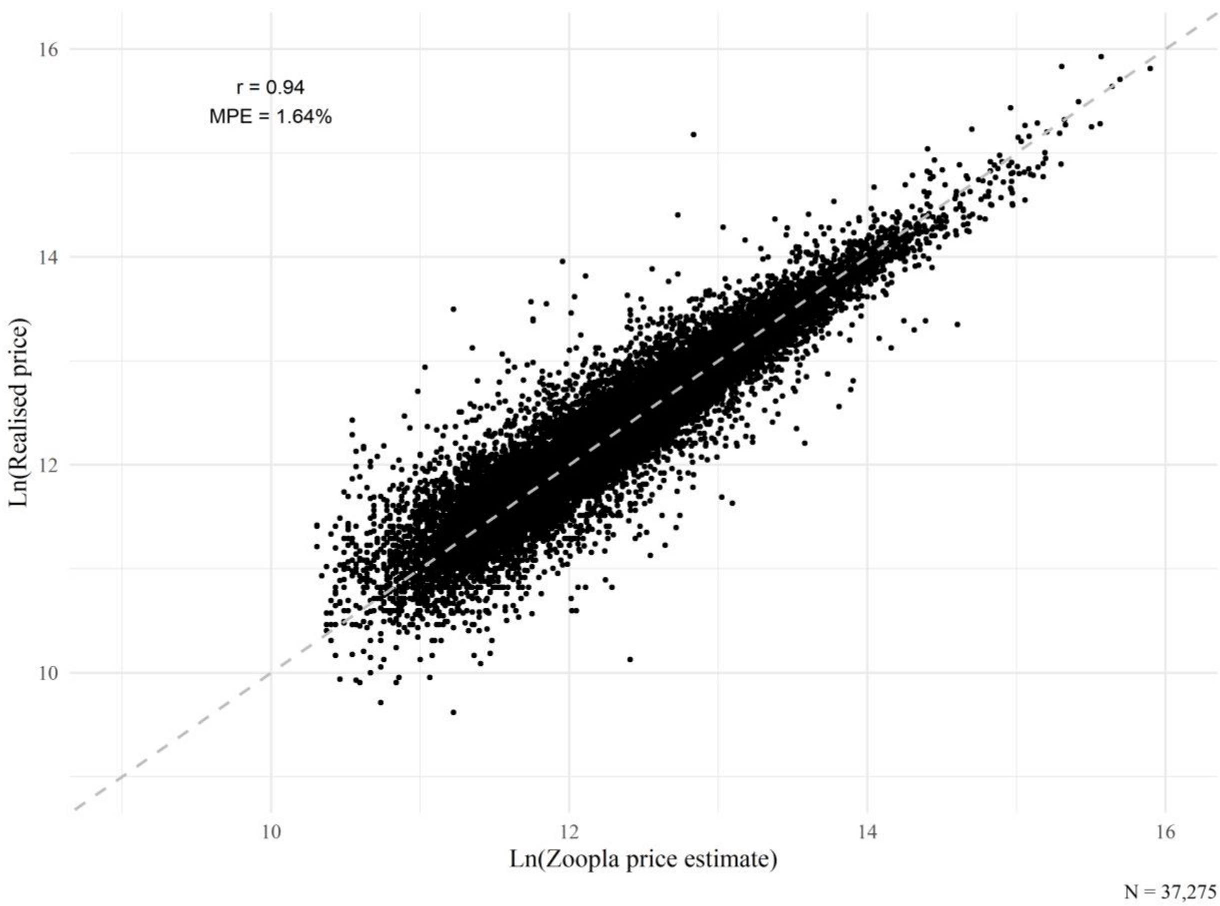
For neighbourhoods, I take the Middle Super Output Area (MSOA) or the nearest equivalent in Scotland and Northern Ireland (Intermediate Data Zones and Super Output Areas respectively). MSOAs are population-weighted census boundaries, containing an average of 7,787 residents.[10] While scholars studying context effects have argued for "personalised" neighbourhoods (Coulton et al., 2013; B. A. Lee et al., 2019), recent work has found that census-based neighbourhoods in

[7] See Zoopla's website for more information on their price estimates: https://help.zoopla.co.uk/hc/en-gb/articles/360006701777-What-is-a-Zoopla-house-price-estimate-.
[8] For a complete list, see information provided on the UK government website: https://www.gov.uk/guidance/about-the-price-paid-data#data-excluded-from-price-paid-data.
[9] The HPI data is publicly available here: https://www.gov.uk/government/collections/uk-house-price-index-reports.
[10] I drop all areas for which there is less than 50 values, leaving a total of 8,481 MSOAs (or 100% of the total number of MSOAs in the UK. Most of Northern Ireland is dropped due to 94.8% of the Data Zones having less than 50 observations.

the US are more closely aligned with subjective perceptions of local characteristics than respondent-defined neighbourhoods (Velez & Wong, 2017).

I favour Zoopla data over the Land Registry for analysis of contemporary inequality given its vastly larger size for 2019 and because it covers the entire UK. Zoopla does not provide statistics for how accurate their estimates are, but I verify this using realised sale prices from the Land Registry for October through November 2019 (N = 37,275). The correlation coefficient between Zoopla estimates and actual prices is very large at 0.94, and the mean percentage error is very small at 1.64% – see Figure 1. Moreover, the Gini coefficients from Zoopla and the Land Registry (2015-2019) are highly correlated at the MSOA-level (r = 0.92), providing assurance that Zoopla data accurately reflects the underlying distribution of housing values.

Figure 1: Relationship between Zoopla estimates and realised house prices



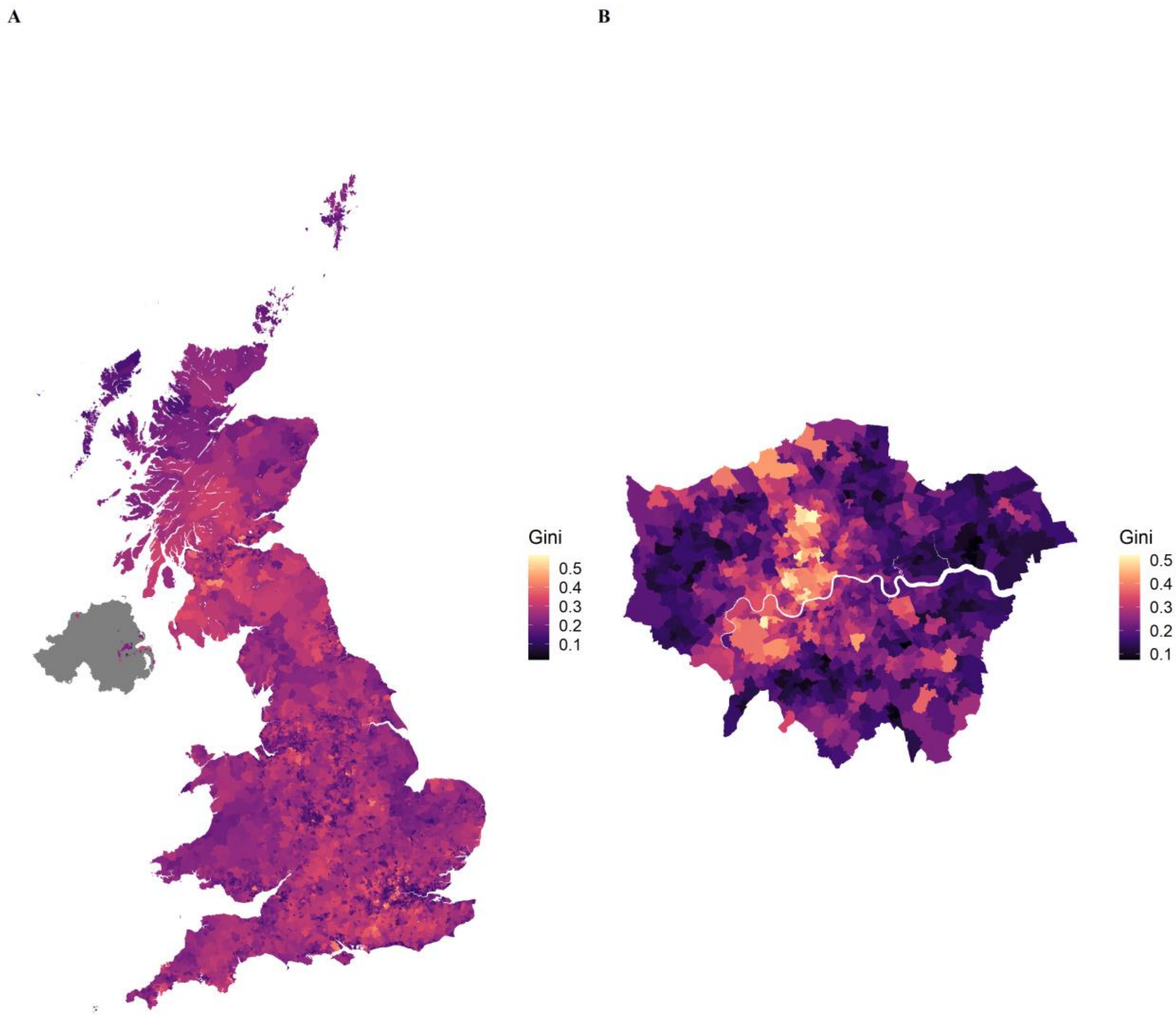
Note: The figure shows Zoopla price estimates at September 2019 that were matched with realised transactions for the subsequent three months from the Land Registry (both log scale). The dashed gray line is the diagonal line of symmetry.

Figure 2 maps MSOA-level inequality in the UK. The Gini ranges from 0.068 to 0.52, with a mean value of 0.225 and standard deviation equal to 0.059. This neighbourhood-level view shows that inequality varies substantially, with urban areas in particular containing both highly equal and highly unequal neighbourhoods, oftentimes existing side-by-side. To help see this, Panel B pulls out London. The UK capital contains the most unequal MSOAs in the country, with areas in the West-end and South-West of the city being particularly unequal. Figure 2 emphasises that taking an aggregate perspective obscures the wide variation that exists with a more local focus. Indeed, the difference between the most unequal and equal neighbourhood in London in terms of the Gini coefficient (0.445) is far larger than the difference between that of the UK and Norway, exemplars of unequal and equal nations respectively, using the Gini of income inequality (0.10; OECD (2020)). This echoes findings in the US which uses census data on incomes – Wheeler & La Jeunesse (2006) show a much greater amount of variation in income inequality within urban neighbourhoods versus across.

Figure 3 shows the change in the Gini coefficient in England and Wales over the twenty year period from 1999-2019 using the Land Registry data. Panel A shows the spatial distribution of change for England and Wales, demonstrating that most MSOAs have seen a reduction in inequality (M = -0.022), oftentimes substantial. However, there is wide variation to experiences of change (SD = 0.035) and, as the map of London (Panel B) demonstrates, change is not evenly spread in space but rather geographically concentrated. In particular, we can see that Central London has experienced increases in neighbourhood inequality versus declines in inequality in the periphery of the capital. Other parts of England have also seen notable increases in inequality, e.g. the North East, the Western part of Cornwall and the Manchester metropolitan region.[11]

[11] The spatial patterns documented for levels and changes of inequality at the MSOA-level are qualitatively similar when using alternative spatial units, in particular Lower Super Output Areas (LSOAs), which are building blocks of MSOAs containing an average of 1,400 residents.

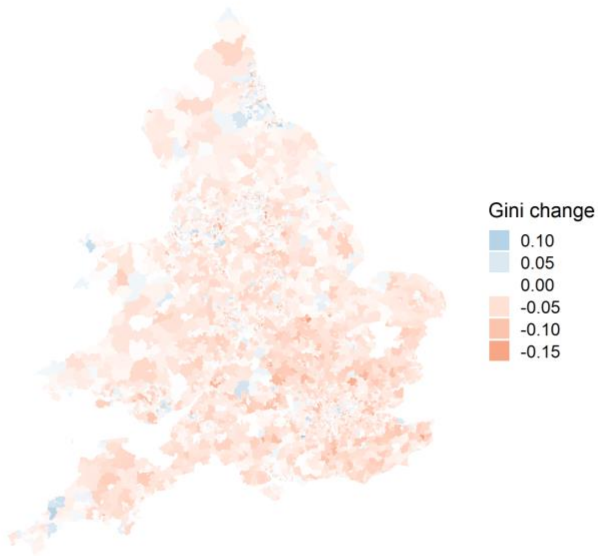
Figure 2: Neighbourhood (MSOA) inequality in the UK



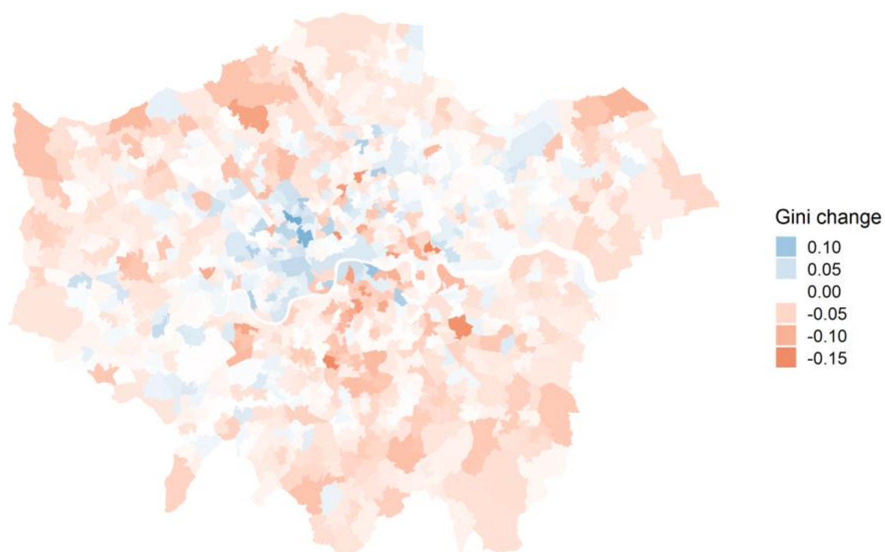
Note: Panel A provides neighbourhood (MSOA)-level Gini coefficients for the UK, and Panel B pulls out London. Areas with less than 50 values in 2019 are taken as missing (gray). All estimates based on house price data from Zoopla.

Figure 3: Change in MSOA-level inequality, England & Wales (1999 to 2019)

A



B



Note: The figure shows change in the absolute value of the Gini coefficient of housing values at the MSOA-level between 1999-2019. Panel A shows England and Wales, and Panel B shows London. Areas with less than 50 transactions in either 1999 or 2019 are taken as missing (gray).

3.2 Perceptions of inequality

To assess whether individual perceptions of local inequality are linked to housing value inequality, I turn to two surveys. First, I exploit Wave 3 of the British Election Study (BES; 2015) which asks respondents to estimate the level of income inequality in their local community on a scale from 1 ("Differences in income are very small") to 7 ("Differences in income are very large") (Fieldhouse, 2017). Wave 3 of BES provides a large sample size (N = 12,150) and geographical markers at the MSOA level.[12] However, BES respondents volunteer to participate and therefore the panel is non-representative of the UK population. Moreover, potentially important correlates of local inequality perceptions are missing, notably Social Dominance Orientation (SDO) – which measures preferences for group-based social inequality (Ho et al., 2015) and has been shown to affect the extent to which people naturalistically attend to and perceive inequality in lab studies (Kteily et al., 2017; Waldfogel et al., 2021), and Personal Relative Deprivation (PRD) – which measures subjective feelings of deprivation relative to similar others (Callan et al., 2011).

To overcome the limitations of BES, and also to ensure the findings are robust, I recruited a panel of respondents from Qualtrics (N = 1,029) during October-November 2019 that is representative of the UK population on age, gender, income, and region. To achieve representativeness on income, I use percentile data provided by HMRC's Survey of Personal Incomes. I ask participants to rate the level of income inequality in their "local neighbourhood." Their response could range from 1-9, with 1 labelled "completely equal" and 9 "completely unequal". Participants provide their postcode information, and so I am able to link responses to MSOAs (as well as more granular geographical areas). I do not ask participants to delineate the boundaries of their "local neighbourhood," but rather leave it up to them to decide for themselves what exactly this constitutes and assume that MSOA boundaries adequately proxy for respondent neighbourhood boundaries. In robustness checks, I vary the definition of neighbourhood in order to mitigate concerns stemming from the Modifiable Areal Unit (MAU) problem (Openshaw, 1984), whereby changes to boundary definitions may substantially affect results.

[12] Data for BES Wave 3 was collected in 2015, so I use the measure of inequality for 2010-2014 based on the Land Registry data. I check whether the inequality measured based on the Zoopla data affects the findings (unreported) – they do not.

3.3 Control variables

There are a number of important individual-level and area-level characteristics that could confound the relationship between local inequality and perceptions of local inequality. For individual-level controls, I include a battery of variables which plausibly affect perceptions:

- Age. Defined as a categorical variable as follows: younger than 35, between 35 and 55, and older than 55 years of age.
- Gender (self-identified by participant).
- Education. Defined as a binary variable for whether the respondent has a university education or not.
- Income. Defined as gross yearly personal income. There are 14 categories for respondents to choose in the BES survey and seven categories for the representative survey, with the income variable taken as the midpoint of the selected category per respondent (£2,500, £7,500, £12.5k, £17.5k, £22.5k, £27.5k, £32.5k, £37.5k, £42.5k, £47.5k, £55k, £65k, £85k, £150k and £7,500, £20k, £30k, £42.5k, £62.5k, £87.5k, £150k respectively).
- Political orientation. An 11-point left-right scale, with higher numbers indicating self-identification as right-wing and vice versa.
- Ethnicity. Self-identified and categorised as either white or non-white.
- Employment status. Defined as employed (full or part-time) and not employed (unemployed, student or not employed for other reasons).

These individual characteristics are common across both the BES and representative surveys. Additionally, for the representative survey I am also able to measure the following:

- Social Dominance Orientation using the eight-item scale developed by Ho et al. (2015). Examples include: “We should work to give all groups an equal chance to succeed,” and “It is unjust to try to make groups equal.” Participants respond using a 7-point Likert scale from ‘Strongly agree’ to ‘Strongly disagree.’ The eight items are then aggregated into an overall numeric score, with larger values indicating greater support for social inequity.

- Personal Relative Deprivation using the five-item scale from Callan et al. (2011). For example, one item is: "I feel dissatisfied with what I have compared to what other people like me have" and participants respond using a 7-point Likert scale as for the SDO scale. The items are also similarly aggregated into an overall numeric score, with higher values indicating respondents feel more relatively deprived.

For area-level controls, I include the median property value and population density (defined as residents per hectare). Both of these variables are logged. Lastly, I also include UK region as a fixed effect, thereby controlling for all unobserved variables which are fixed at the region level (e.g. London- or Scotland-specific attitudes towards inequality). Descriptive statistics for all variables across both surveys are provided in Figure A.1 in the Annex.

4 Salience of housing value inequality

4.1 Analytical strategy

In order to examine associations between housing value inequality and subjective perceptions, I specify the following random effects model:

$$y_{ij} = \alpha + \beta X_{ij} + \gamma Gini_j + \delta Z_j + Region_i + \theta_j + \epsilon_{ij}$$

where y_{ij} is the subjective assessments of inequality for individual i in area j (I treat the assessments as a continuous rather than discrete numeric variable), α is the intercept, X_{ij} is the vector of individual-level controls, Z_j is the vector of area-level controls (median property value and population density), $Region_i$ is fixed effects for UK region, θ_j is the random intercept error term, and ϵ_{ij} is the individual error term. $Gini_j$ is housing value inequality for area j, and therefore γ is our coefficient of interest as the estimate of the effect of neighbourhood inequality on subjective perceptions.

A random intercept model is appropriate for understanding contextual effects where individuals are nested within neighbourhoods (and thus non-independent). Specifying this model allows us to estimate the effect of local inequality and other neighbourhood-level variables on individual perceptions of inequality, while also controlling for other, unspecified contextual effects (absorbed by θ_j) which affect perceptions in common within neighbourhoods.

In robustness checks, I vary the spatial unit of analysis to mitigate concerns arising from the Modifiable Areal Unit (MAU) problem (Openshaw, 1984) – rather than MSOAs, I examine a more granular geographic area (LSOAs) made possible by the representative survey, as well as larger spatial units that might still reasonably proxy for 'local area' (ONS Built-Up Areas – BUAs). I also specify a spatial regression to account for the characteristics of neighbouring MSOAs, which may influence individual perceptions of local inequality – see Section 4.3.

4.2 Regression results

Table 1 provides results for the BES study. Column 1 is the Gini without area or individual-level control variables (but inclusive of region fixed effects), and Column 2 includes all controls. The coefficient on the Gini of housing values is statistically significant – there is an association between MSOA-level housing value inequality and perceptions of local income inequality. A one standard deviation increase in the Gini is associated with an expected increase of 0.108 and 0.084 of a standard deviation respectively for Columns 1 and 2.

Table 2 provides the results for the representative survey. Columns 1 and 2 are for MSOA-level housing value inequality without the additional covariates (SDO and PRD), and Columns 3 includes these as well. I find the coefficient on the Gini to be significant and substantive in size for each model. Housing value inequality is associated with perceptions of local inequality. The standardised coefficient estimates are generally larger in size as that found in analysis of the BES survey (0.095 for the full model in Column 3). In other words, a one standard deviation increase in inequality (0.051) is associated with approximately 10% of a standard deviation increase in perceptions of inequality (or 0.182 of a notch on the 9-point scale). The inclusion of the additional controls does not substantively affect the point estimates for housing value inequality. While SDO does not seem to be important, PRD is strongly associated with perceptions of local inequality, with those that feel more relatively deprived perceiving substantially more inequality (coefficient of 0.145 in Column 3).

Table 1: Perceptions of local income inequality – British Election Study survey

	Dependent variable:	
	Perceived local inequality	
	(1)	(2)
Gini	0.108***	0.084***
	(0.010)	(0.013)
Median house value (log)		0.049***
		(0.018)
Density (log)		-0.035***
		(0.012)
Income		0.025**
		(0.011)
Political orientation (left-right)		-0.150***
		(0.010)
University education		0.104***
		(0.021)
Female		0.022
		(0.021)
Age 35-55		0.049*
		(0.029)
Age 55+		0.074***
		(0.028)
White		0.001
		(0.048)
Employed		0.024
		(0.022)
Region fixed effects	Y	Y
Observations	12,149	9,477
Log Likelihood	-17,174.190	-13,294.750
Akaike Inf. Crit.	34,356.380	26,637.500
Bayesian Inf. Crit.	34,386.000	26,809.260
Note:	*p<0.1; **p<0.05; ***p<0.01	
	The table provides estimates for the relationship between local inequality at the MSOA-level and perceived local income inequality	
	All continuous variables are scaled, and standard errors in parentheses	

Table 2: Perceptions of local income inequality – representative survey

	Perceived local income inequality		
		MSOA-level	
	(1)	(2)	(3)
Gini	0.075**	0.099***	0.095**
	(0.032)	(0.038)	(0.037)
Median house value (log)		-0.041	-0.023
		(0.057)	(0.057)
Density (log)		0.020	0.014
		(0.039)	(0.039)
Income		-0.003	0.016
		(0.034)	(0.034)
Political orientation (left-right)		-0.095***	-0.073**
		(0.032)	(0.034)
University education		0.051	0.071
		(0.067)	(0.067)
Female		0.062	0.059
		(0.071)	(0.071)
Age 35-55		0.204***	0.215***
		(0.077)	(0.076)
Age 55+		0.107	0.189**
		(0.094)	(0.095)
White		0.038	0.012
		(0.124)	(0.123)
Employed		0.018	0.009
		(0.072)	(0.071)
SDO			-0.046
			(0.035)
PRD			0.145***
			(0.033)
Region fixed effects	Y	Y	Y
Observations	1,003	986	986
Log Likelihood	-1,424.713	-1,409.320	-1,403.581
Akaike Inf. Crit.	2,877.426	2,866.640	2,859.161
Bayesian Inf. Crit.	2,946.176	2,984.088	2,986.396

Note: *p<0.1; **p<0.05; ***p<0.01

The table provides estimates for the relationship between local inequality at the MSOA-level and perceived local income inequality

All continuous variables are scaled, and standard errors in parentheses

4.3 Robustness checks

Next, I check whether the relationship between housing value inequality and perceptions of local inequality are sensitive to the spatial unit and empirical specification chosen. First, I vary the definition of geography – it might be that the MSOA-level is not a suitable approximation for local neighbourhood. Moreover, varying the level at which inequality is measured mitigates concerns around the MAU, that the relationship observed in the results above are sensitive to boundary choices. In Table 3 below, I measure inequality and other area variables at both a more granular and more coarse geographical unit. Column 1 uses the Lower Super Output Area (LSOAs) – these are population-weighted building blocks of MSOAs with an average population of roughly 1,400 (there are a total of 42,619 LSOAs in the UK). Columns 2-4 of Table 3 instead uses Built-Up Areas (BUAs). These are ONS defined spatial units that correspond to contiguously inhabited areas (settlements within 200 meters are linked, covering roughly 95% of the population of England and Wales), from small hamlets to the largest cities (i.e. London is one single BUA). Because large cities are unlikely to represent local neighbourhoods for survey respondents, Columns 3 and 4 reduce the sample to only those respondents who do not live in large cities (defined as at least 1 million inhabitants) or all cities (defined as at least 100,000 inhabitants). In each column, the coefficient on the Gini of housing values is positive and statistically significant, demonstrating that the relationship between housing value inequality and perceptions of inequality holds for these alternative spatial units. The coefficient values range from 0.084 for LSOAs and 0.261 for BUAs when excluding all cities. The latter coefficient size suggests BUAs might be a good proxy for local neighbourhoods outside cities, and that our lack of precision in defining neighbourhoods for each respondent is perhaps attenuating the estimated association between local housing inequality and subjective perceptions when estimating inequality at the MSOA-level.

Second, the random intercept model presented above does not account for spatial effects. Given that neighbourhood inequality and other area characteristics are not randomly distributed in space (see Figure 2), it could be that the level of inequality in neighbouring MSOAs also has an effect on individual perceptions of inequality. Spatial effects may be accounted for by using BUAs as the spatial unit analysis given that, by construction, neighbouring BUAs are typically separated in space via physical distance, and so inhabitants of one BUA might not visit or be influenced by neighbouring BUAs as much as they would neighbouring MSOAs, but nevertheless these alternative econometric specifications ensure that the coefficient estimates are not biased by spatial dependence, and that standard errors are not underestimated (Anselin, 2009). To control for spatial effects, I specify a spatial lag model with random intercepts. This replicates the results in Table 2 but includes spatial lags for inequality, the median property price, and population density – taken as the average of all adjoining MSOAs (i.e. the Queen configuration). I also estimate a spatial error model (SEM), which incorporates spatial dependence in the residuals rather than as spatial lags. The results are presented in Figure A.2 – the estimated coefficient for the Gini remains positive and statistically significant (0.098 and 0.093 for these spatial models respectively).

Lastly, I include additional controls to address the possibility that the proportion of rentals in a local neighbourhood, which is plausibly correlated with housing value inequality due to the nature of the underlying data, affects perceptions of local inequality. I add the following variables to the baseline regression: the percentage of properties rented in each MSOA (taken from the 2011 census), and the predicted percentage of properties in the local area that are rented (elicited by subjects during the representative survey). Figure A.3 in the Annex provides these results. The objective percentage of rented properties is not significant, but the subjective percentage of rented properties is statistically significant. The addition of these variables does not qualitatively affect the results.

Table 3: Robustness check – alternative spatial units of analysis

	Perceived local income inequality			
	LSOA	BUA	BUA (excluding big cities)	BUA (excluding cities)
	(1)	(2)	(3)	(4)
Gini	0.084**	0.108**	0.161**	0.261***
	(0.036)	(0.055)	(0.068)	(0.095)
Median house value (log)	-0.029	-0.029	-0.013	0.037
	(0.052)	(0.076)	(0.084)	(0.106)
Density (log)	0.022	-0.047	-0.031	0.025
	(0.039)	(0.052)	(0.054)	(0.067)
Income	0.018	0.023	0.057	0.116*
	(0.034)	(0.035)	(0.042)	(0.061)
Political orientation (left-right)	-0.066*	-0.062*	-0.064	-0.041
	(0.035)	(0.035)	(0.042)	(0.059)
University education	0.078	0.100	0.103	0.077
	(0.067)	(0.068)	(0.080)	(0.114)
Female	0.042	0.056	0.038	0.162
	(0.071)	(0.072)	(0.086)	(0.123)
Age 35-55	0.200***	0.237***	0.143	0.172
	(0.077)	(0.078)	(0.092)	(0.135)
Age 55+	0.195**	0.211**	0.133	0.043
	(0.095)	(0.098)	(0.114)	(0.159)
White	0.004	0.034	-0.141	0.195
	(0.123)	(0.126)	(0.194)	(0.366)
Employed	-0.001	-0.054	-0.076	-0.185
	(0.072)	(0.073)	(0.086)	(0.122)
SDO	-0.045	-0.052	-0.064	0.020
	(0.035)	(0.035)	(0.042)	(0.059)
PRD	0.155***	0.144***	0.143***	0.074
	(0.033)	(0.033)	(0.038)	(0.055)
Region fixed effects	Y	Y	Y	Y
Observations	982	942	704	346
Log Likelihood	-1,396.876	-1,343.782	-1,020.058	-500.715
Akaike Inf. Crit.	2,845.752	2,739.563	2,090.115	1,051.429
Bayesian Inf. Crit.	2,972.882	2,865.611	2,204.035	1,147.590

Note: *p<0.1; **p<0.05; ***p<0.01

The table provides estimates for the relationship between local inequality at different spatial levels and perceived local income inequality

Cities are defined as those urban areas with at least 100k inhabitants. Big cities are defined as those with at least 1mn inhabitants.

All continuous variables are scaled, and standard errors in parentheses

5 Discussion and conclusion

In this paper, I introduce a novel measure of local, salient economic inequality. In the absence of high quality, granular information on incomes or wealth, I exploit two large datasets on the value of houses for a combined 26.6 million UK addresses. This data makes it possible to measure economic inequality at the neighbourhood level in the UK for the first time. Importantly, I demonstrate that this measure is associated with people's perceptions of inequality across two surveys and controlling for important individual and contextual factors.

A brief descriptive analysis reveals a prevalence of extreme levels of inequality side-by-side with areas of relative equality within urban settings. In other words, the lived experience of inequality is often itself *unequal*. I also document how local inequality has changed over the period 1999-2019. Inequality has declined on average across neighbourhoods in England and Wales. This average decline comes with a wide variance and spatial clustering – while most parts of England and Wales saw reductions in inequality, other parts saw substantive increases, especially in Central London and other urban agglomerations, such as Greater Manchester and the North East. This is a stark finding when compared with trends at the national level, where inequality (whether measured by housing values or incomes) has been broadly static over the same period of time. For example, data from the World Inequality Database (WID) suggests that pre and post-tax income inequality has been flat over the same period (see the data provided online here: https://wid.world/). The UK-level housing value inequality is similarly flat. This highlights the benefits of taking a spatially disaggregated view – there is much change happening beneath the surface. What explains these local patterns of inequality change in the UK? Some possible answers include structural trends in housing demand, with people increasingly preferring to live in city centers rather than suburbs. A carefully considered answer to this question is outside the scope of this paper but warrants scholarly attention.

Using housing value inequality as a proxy for economic inequality clearly has some downsides, however. For one, estimates of inequality based on housing values may not correspond with more traditional approaches to measuring inequality, e.g. via surveys or administrative data providing information on actual income and wealth. In particular, the housing data does not distinguish between houses that are owned or rented. Nevertheless, I argue that this does not matter from a perceptual perspective, and perceptions of inequality are key drivers of attitudes and behaviour. For this reason, I test the hypothesis that individuals make inferences about the level of actual income inequality by what they observe around them in the form of housing.

Across two surveys, Wave 3 of the British Election Study and a representative survey of UK respondents, I show that housing value inequality is indeed substantively associated with perceptions of inequality. In other words, seeing housing value inequality (or lack thereof) affects people's beliefs about local income inequality. This is an important finding, not only as it assuages concerns around using housing value data to measure inequality – individuals receive the 'treatment' (Newman et al., 2018) – but also because it represents the first evidence of the importance of features of the built environment feeding into perceptions of economic inequality.

Of course, the built environment is only one influence on people's perceptions of inequality (Minkoff & Lyons, 2019). While the estimated relationship with perceptions is relatively large in size, representing approximately 10% of a standard deviation, slightly larger than the effect of political orientation, there are likely other important factors which I have not been able to include here, e.g. interpersonal networks and media influence. Another important factor might be the areas where individuals spend a lot of time outside their home neighbourhood, for example by travelling for work. Future research might try to take a comprehensive approach in understanding perceptions of inequality, exploring how different possible channels come together and interact with place-based and individual-level characteristics.

This paper uses a large volume of alternative data to estimate economic inequality. In that sense, the work fits in with other papers which use alternative data sources, for example images, to predict economic variables at local levels. For instance, research has utilised Google Street View and neural networks to accurately predict average neighbourhood income in the US (Gebru et al., 2017) and multiple deprivation in the UK at the LSOA-level (Suel et al., 2019). Future work might seek to utilise these methods and data sources, perhaps combined with subjective assessments of inequality as presented here, or alternatively as elicited through other sources (Dubey et al., 2016; Naik et al., 2016), to estimate economic discrepancies at granular geographical levels.

The measures developed here have been made publicly available (https://github.com/jhsuss/uk-local-inequality) to support further research. For example, the data might be used to shed light on the trends and levels of local inequality in the UK, or to answer research questions which seek to understand the consequences of economic inequality. In particular, there is ongoing scholarly debate regarding whether inequality affects voter turnout (Cancela & Geys, 2016; Stockemer & Scruggs, 2012), consumer borrowing (Coibion et al., 2014; Payne et al., 2017), and pro-social behaviour (Côté et al., 2015; Schmukle et al., 2019), to name a few. These studies have been generally confined to estimating the effects of spatially aggregated income inequality, and it is known that people widely misperceive aggregate levels of inequality (Gimpelson & Treisman, 2018; Hauser & Norton, 2017; Norton & Ariely, 2011). Using instead the measure introduced here, or other spatially-granular and salient measures of inequality, would entail looking at the problem from a new, more contextually-relevant perspective.

Annex

Table A.1: Descriptive statistics for survey data

	BES survey					
Statistic	N	Min	Median	Mean	Max	St. Dev.
Inequality perceptions	12,150	1	5	4.81	7	1.41
Gini	12,149	0.08	0.23	0.23	0.52	0.06
Median house value	12,150	56,000	203,000	246,928.20	2,024,000	159,559.70
Density	12,150	0.01	21.20	29.60	247.20	33.41
Income	9,666	2,500.00	22,500.00	24,654.46	150,000.00	21,452.30
Political orientation	11,890	0.00	2.50	3.00	10.00	2.21
University education	12,150	0	0	0.40	1	0.49
Female	12,150	0	0	0.47	1	0.50
Age < 35	12,150	0	0	0.21	1	0.41
35 < = Age < = 55	12,150	0	0	0.31	1	0.46
Age > 55	12,150	0	0	0.48	1	0.50
White	12,144	0.00	1.00	0.95	1.00	0.23
Employed	12,150	0	0	0.43	1	0.49

	Representative survey					
Statistic	N	Min	Median	Mean	Max	St. Dev.
Inequality perceptions	1,029	1	5	5.50	9	1.82
Gini	1,003	0.08	0.21	0.22	0.36	0.05
Median house value	1,029	63,000	183,000	220,204.60	829,000	122,330.60
Density	1,003	0.04	26.10	32.54	181.80	30.88
Income	1,029	7,500	20,000	29,754.62	150,000	23,348.29
Political orientation	1,029	0	5	5.18	10	2.10
University education	1,029	0	0	0.44	1	0.50
Female	1,029	0	1	0.54	1	0.50
Age < 35	1,029	0	0	0.32	1	0.47
35 < = Age < = 55	1,029	0	0	0.39	1	0.49
Age > 55	1,029	0	0	0.28	1	0.45
White	1,029	0	1	0.92	1	0.26
Employed	1,029	0	1	0.63	1	0.48
SDO	1,029	1	3.4	3.23	7	0.99
PRD	1,029	1	3.8	3.74	7	1.06

Table A.2: Robustness check – spatial regression models

	Perceived local income inequality	
	Spatial lag model	Spatial error model
	(1)	(2)
Gini	0.099**	0.103***
	(0.050)	(0.038)
Median house value (log)	0.003	-0.054
	(0.106)	(0.059)
Density (log)	0.028	0.008
	(0.063)	(0.039)
Income	0.021	0.019
	(0.035)	(0.033)
Political orientation (left-right)	-0.084**	-0.070**
	(0.035)	(0.034)
University education	0.059	0.066
	(0.069)	(0.066)
Female	0.051	0.062
	(0.074)	(0.070)
Age 35-55	0.215***	0.219***
	(0.079)	(0.075)
Age 55+	0.229**	0.198**
	(0.096)	(0.091)
White	-0.018	-0.002
	(0.124)	(0.121)
Employed	-0.032	-0.017
	(0.093)	(0.089)
SDO	0.032	0.050
	(0.036)	(0.034)
PRD	-0.158***	-0.146***
	(0.034)	(0.032)
Gini (lag)	0.043	
	(0.061)	
Median house value (lag)	-0.054	
	(0.123)	
Density (lag)	-0.019	
	(0.066)	
Region fixed effects	Y	Y
Observations	917	986
Log Likelihood	-1,305.183	-1,365.938
$sigma^2$		0.934
Akaike Inf. Crit.	2,666.366	2,783.876
Bayesian Inf. Crit.	2,801.357	
Wald Test		1.252 (df = 1)
LR Test		1.246 (df = 1)
Note:	*p<0.1; **p<0.05; ***p<0.01	
	The table provides estimates for the relationship between local inequality at the MSOA-level and perceived local income inequality	
	All continuous variables are scaled, and standard errors in parentheses	

Table A.3: Robustness check – objective and subjective proportion renting

	Perceived local income inequality		
	(1)	(2)	(3)
Gini	0.082**	0.090**	0.085**
	(0.038)	(0.037)	(0.038)
Median house value (log)	0.013	0.011	0.024
	(0.061)	(0.057)	(0.061)
Density (log)	-0.015	-0.003	-0.014
	(0.043)	(0.039)	(0.042)
Income	0.019	0.023	0.024
	(0.034)	(0.034)	(0.034)
Political orientation (left-right)	-0.070**	-0.069**	-0.068**
	(0.034)	(0.034)	(0.034)
University education	0.071	0.082	0.082
	(0.067)	(0.066)	(0.066)
Female	0.061	0.047	0.049
	(0.071)	(0.070)	(0.070)
Age 35-55	0.225***	0.236***	0.239***
	(0.077)	(0.076)	(0.076)
Age 55+	0.204**	0.236**	0.239**
	(0.095)	(0.095)	(0.095)
White	0.026	0.020	0.025
	(0.123)	(0.122)	(0.123)
Employed	0.011	0.018	0.018
	(0.071)	(0.071)	(0.071)
SDO	-0.046	-0.044	-0.044
	(0.035)	(0.035)	(0.035)
PRD	0.142***	0.131***	0.130***
	(0.033)	(0.033)	(0.033)
Local rent (% actual)	0.067		0.027
	(0.042)		(0.044)
Local rent (% subjective)		0.122***	0.116***
		(0.033)	(0.035)
Region fixed effects	Y	Y	Y
Observations	986	986	986
Log Likelihood	-1,404.558	-1,399.516	-1,401.534
Akaike Inf. Crit.	2,863.117	2,853.032	2,859.067
Bayesian Inf. Crit.	2,995.245	2,985.160	2,996.090

Note: *p<0.1; **p<0.05; ***p<0.01

The table provides estimates for the relationship between local inequality at the MSOA-level and perceived local income inequality

All continuous variables are scaled, and standard errors in parentheses

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