The London School of Economics and Political Science

Local economic inequality in the UK: patterns, determinants, and behavioural consequences

Joel H. Suss

A thesis submitted to the Department of Psychological and Behavioural Science of the London School of Economics and Political Science for the degree of Doctor of Philosophy, London, March 2021

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consists of 48,324 words (including references and annexes).

Statement of co-authored work

I confirm that Chapter 5 was co-authored with Thiago R. Oliveira. I confirm that I wrote 67% of the paper and contributed 90% of the necessary research work.

Abstract

I develop a novel, geographically granular measure of economic inequality in the UK based on data covering tens of millions of residential properties. The size of this data allows me to describe and understand the consequences of local inequality in the UK for the first time.

The first paper in my thesis explores patterns of local economic inequality, both contemporary levels and changes over the last couple decades. The paper also examines whether salient features of the local environment affect people's perceptions of economic inequality. Across two surveys, I find that discrepancies in housing quality are indeed a salient aspect affecting people's perceptions.

I then examine the determinants of inequality at different spatial resolutions, from the city down to the neighbourhood level. I find that local composition of skills, housing tenure, and amenities are all important factors.

The third, fourth and fifth papers in my thesis examine the consequences of local inequality for a number of important individual and group behaviours. First, I examine whether local inequality affects pro-social spending, providing new insight into a question that has produced conflicting findings. Across two studies covering the US and UK, I find that local inequality interacts positively with income – higher income individuals are more generous in areas of higher inequality, probably because they come into contact with poorer individuals more often.

Second, in a paper co-authored with Thiago Oliveira, I explore whether variation in neighbourhood-level inequality in London affects the prevalence of police stop and search behaviour. We find a positive relationship, supporting criminological theories on police behaviour and social order maintenance.

Finally, combining data on economic inequality with data on local ethnic composition from the UK census, I examine whether patterns of residential diversity and segregation affects political behaviour. Using Brexit as a case study, I find strong evidence in support of contact rather than conflict theory – neighbourhood economic and social diversity reduces support for Brexit, but the opposite is true for segregation.

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Acknowledgments

To my loving, patient wife, Kate Laffan – I could not have done this without you, nor can I really do much of anything without you! I am very lucky that we've been brought together, large distances and the Atlantic Ocean notwithstanding.

To my little lady, Aida, you have helped me more than you now know. We are blessed with your bright smile, laughter and de-stressing abilities.

To my parents, Chana and Sam, I am glad you instilled in me an appetite for education and learning that has not yet been satiated. I am grateful for you unconditional support, and the generosity that only parents can provide. I promise to pass this on to Aida and whoever else is to come!

To my brothers, Matty and Jonathan, thank-you for helping and guiding me through life. To my cousin and best-man, Kenny, thank-you for exercising my argumentative skills with respect to this PhD topic. I promise to argue less in future…

Thank-you John Hills for inspiring me and supervising this PhD. I am very grateful to have been able to know you and learn from you while you were here with us.

Thank-you Paul Dolan for supervising this PhD and for all your support along the way.

Thank-you to the LSE International Inequalities Institute for providing a diverse and nurturing PhD environment, and particularly to Niki Lacey and David Soskice for convening the wonderful seminar that brought all us PhD students together. Thank-you to Tania Burchardt and the LSE Centre for Analysis of Social Exclusion (CASE) for all your advice and support, and to Liz Mann for putting up with me in the ~~waiting-room~~ office over the years.

And thank-you to all the people over these past few years, my friends and colleagues too numerous to list by name, who have supported me with conversation, encouragement, laughter and love. I appreciate everything, and am looking forward to having a lot more time to spend with you all!

Funding

I am grateful to the Leverhulme Trust for supporting this PhD in association with the LSE International Inequalities Institute.

I am also grateful to the LSE Marshall Institute for providing research funding.

1 Introduction

Economic inequality is widely considered to be among the defining policy issues of our time. In the United Kingdom (UK), recent years have seen economic disparities become the focus of much interest from both members of the public and policymakers, for example giving rise to the Occupy London movement in 2011 (Haldane, 2012; Yagci, 2017), and to the foundation of the UK Wealth Tax commission in 2020 (Advani, Chamberlain, et al., 2020). The widespread interest in the topic of economic inequality reflects the fact that both income and wealth are distributed relatively unequally in the UK. Overall, the average income of the richest quintile is estimated to be approximately six times that of the poorest (ONS, 2021), and the level of wealth inequality is almost twice that of income (Crawford et al., 2016), if not more (Advani, Bangham, et al., 2020). Examinations of regional inequality paint an even starker picture – statistics suggest that the UK is one of the most regionally unbalanced countries in the developed world (Carrascal-Incera et al., 2020; McCann, 2020).

Economic inequality has been the focus of much scholarly attention. Broadly speaking, research on economic inequality can be divided into two categories: exploration of the *causes* of inequality, and examination of its *consequences*. For example, in the former category, Thomas Piketty famously described trends and causes of country-level inequality in his book, *Capital in the Twenty-First Century* (2014). Other studies focus more specifically on the causes of inequality for individual countries (Alvaredo et al., 2018; Marchand et al., 2020; Piketty & Saez, 2014). For example, in the UK research has examined links between fiscal (Blundell et al., 2018; Hills, 2015; Joyce & Sibieta, 2013) and monetary policies (Mumtaz & Theophilopoulou, 2017) and inequality.

Studies focusing on the consequences of inequality have become relatively more numerous in recent decades (Cavanaugh & Breau, 2018), as concerns about the implications of rising inequality have risen. For example, papers have looked at the consequences of inequality for health (Kawachi & Kennedy, 1999; Pickett & Wilkinson, 2015; Subramanian & Kawachi, 2004; Wagstaff & Van Doorslaer, 2000), subjective wellbeing (Alesina et al., 2004; Delhey & Dragolov, 2014; Ferrer-i-Carbonell, 2005; Graham & Felton, 2006; Oishi et al., 2011), and social trust (Gustavsson & Jordahl, 2008; Hastings, 2018; Olivera, 2015; Uslaner & Brown, 2005), among many other outcomes.

A shortcoming of the literature exploring the consequences of inequality for behavioural outcomes is that scholars tend to treat inequality as a macro phenomenon, with the geographical resolution at which it is typically measured at the country or region-level. 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.

Indeed, this thesis aims to re-focus attention on local inequality and its implications for important social, economic and political behaviours. In what follows, I first provide the theoretical and conceptual basis for focusing on local economic inequality. I then provide an overview of the papers which comprise this thesis before briefly discussing the country of focus.

1.1 Why local inequality matters

The central contention of this thesis is that local inequality has important behavioural implications. But why would local inequality matter? I aim to answer this question in this section, making use of theoretical and conceptual work, as well as nascent empirical findings, from across the social sciences.

To begin with, it is worth taking a step back and considering 'neighbourhood-effects' more broadly, i.e. whether local contexts matter in general. There are a number of separate but related strands of literature which testify to the importance of local contexts for individual outcomes. In other words neighbourhoods matter. Local contexts have been shown to affect a range of 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). Work on the potential causal mechanisms running from neighbourhoods to individual outcomes finds that, among other pathways, local contexts foster social networks, are sources of social contagion and comparison, and serve as primary arenas for observation and accumulation of knowledge about the world (G. C. Galster, 2012).

Seen from the vantage point of the broader 'neighbourhood effects' literature, local economic discrepancies are an important contextual feature. The identified 'neighbourhood' mechanisms are therefore channels through which local inequality might matter for individual behaviour. This view is supported by social psychological theoretical work on relative deprivation (Runciman, 1966) and social comparison processes (Festinger, 1954).

Relative deprivation theory highlights the importance of local comparisons and reference groups for individual emotional and behavioural outcomes (see H. J. Smith et al., 2012 for a systematic review). Individuals compare themselves with other people or groups around them, and in this way those living in unequal neighbourhoods and who are relatively worse off may feel deprived compared with similar individuals living in a more equal setting. Feelings of deprivation then translate into negative emotional responses, e.g. anger, and affect inter-group relationships (H. J. Smith & Huo, 2014), economic behaviour (Kim et al., 2017), and political preferences (Brown-Iannuzzi et al., 2015). From this perspective, social comparison processes are fundamental to how we make sense of our standing in our communities and societies, and local neighbourhoods are a primary setting where these comparisons are made.

Relatedly, the field of economics has also incorporated the idea of local social comparisons in relation to income discrepancies, just with different terminology and methodology. Research on the 'relative income hypothesis' (Duesenberry, 1949) finds that what our neighbours earn has an influence on how we feel and our economic behaviour (Hagerty, 2000; A. Kuhn, 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. A. Kuhn (2011) find that households are more likely to increase consumption when their neighbour wins the lottery.

The literature on inter-group contact also provides valuable insight on the importance of local inequality. Contact theory suggests that local ethnic or racial diversity reduces the distance between different groups, fostering social networks and mitigating stigmatisation (Allport et al., 1954; Pettigrew et al., 2011; Pettigrew & Tropp, 2006), whereas 'conflict' theory suggests the exact opposite (Blalock, 1967). These theories can be extended also to the economic dimension, where inequality has been argued to increase social distance between economic groups (Côté et al., 2015; Duquette & Hargaden, 2019), inducing greater stigmatisation (Durante & Fiske, 2017; Lamont et al., 2014) and class 'awareness' (Newman et al., 2015). On the other hand, positive inter-group contact between rich and poor, which might arise from economically integrated neighbourhoods (G. Galster, 2007), might reduce misconceptions by promoting cross-class social network formation and understanding (Danny Dorling, 2017).

These various strands of theoretical work all suggest an important role for local economic inequality, via what I will call the *interpersonal* channel. Put simply, local inequality affects the social networks and social comparisons that people make.

Note that the above discussion suggests that the effect of local inequality on behaviour is ambiguous, i.e. it might lead to 'good' or 'bad' outcomes. To bring this to life, let's take as a hypothetical thought experiment two rich individuals who are the same in every respect except one lives in an economically heterogeneous neighbourhood while another lives in a gated community segregated from poorer individuals. We might expect that the first rich person develops greater empathy for those poorer and is more generous as a result of being in constant contact with them, especially if their circle of friends includes those relatively poorer (see Chapter 4). On the other hand, local inequality might elicit behaviour which might not be beneficial – for example, as the theoretical framework discussed in Chapter 5 suggests, police might be more likely to exert 'social control', stopping and searching individuals more frequently in the presence of higher local inequality.

Either way, whether 'good' or 'bad,' the interpersonal channel suggest that local economic discrepancies matter for individual behaviour. A nascent body of empirical work reinforces this argument, demonstrating that local inequality does indeed affect a broad range of social, political and economic behaviours, for example support for redistributive policies (Sands, 2017; Sands & Kadt, 2020), intergenerational mobility (Chetty & Hendren, 2018b, 2018a), subjective wellbeing (Carr, 2013; Ifcher et al., 2019), crime (Brush, 2007; Kelly, 2000; Morenoff et al., 2001; Whitworth, 2013), and labour market outcomes (Ioannides & Datcher Loury, 2004).

Moreover, experimental evidence spanning multiple disciplines – sociology, political science, economics, and the behavioural 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., 2015; B. K. Payne et al., 2017; Trump, 2016). While these experimental studies are 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. Taken together, it is clear that local contexts matter, and the distribution of economic resources within local contexts especially so.

1.2 A critique of macro-level inequality measurement

Nevertheless, despite the theoretical arguments and empirical findings outlined above, in many social science disciplines where the outcome of interest is some individual or group-level behaviour, inequality is oftentimes measured at a much more aggregated geographical level. Cavanaugh & Breau (2018) confirm this point by carrying out a systematic review of inequality studies and noting the spatial level of analysis used. The authors find that there are far fewer studies conducted below the country and regional level than at or above.

This is a problem for understanding the effect of inequality on behaviour for two reasons: studies which focus on macro inequality implicitly assume either that i) the macro-level is the appropriate level at which inequality is 'treated', or that ii) people are generally aware of or accurately perceive national-level inequality. There are reasons to doubt these assumptions.

First, a more disaggregated focus can reveal variation that is obscured by macro-level measures of inequality. Should we expect the experience of inequality in London to be similar to that of nearby Luton, for example? According to estimates of economic inequality presented below in Chapter 2, inequality in London (the most unequal city in the UK) is 74.5% higher than Luton (the most equal). The absolute difference in the Gini coefficient, a commonly used measure of inequality, is 0.152, larger than the difference between that of the United Kingdom and Norway (0.10)[1], exemplars of unequal and equal countries respectively. Zooming in further, the difference between the most unequal and equal neighbourhood in London, taken as the Middle Super Output Area (MSOA)[2], is a whopping 0.45, demonstrating the very different contextual circumstances residents face within the same metropolitan setting. Given this wide sub-national variation, it is questionable whether national-level inequality is an appropriate spatial unit for understanding the impact of inequality on behaviour.

Second, while individual judgments about national inequality are important for their attitudes and behaviour, e.g. by affecting their social mobility or opportunity beliefs (McCall et al., 2017), and redistributive preferences (Cruces et al., 2013; Hauser & Norton, 2017; A. Kuhn, 2019), it is not the case that individuals have an accurate understanding of the actual extent of inequality in

[1] Author's calculations from OECD (2020) figures for income inequality in 2019, available publicly here: https://data.oecd.org/inequality/income-inequality.htm.

[2] MSOAs are census areas that are roughly similar in population size (M = 7787, SD = 1600), and are built up from constituent parts which are meant to conform to natural boundaries.

society. Indeed, people are wildly inaccurate when it comes to judging inequality (Chambers et al., 2014; Gimpelson & Treisman, 2018; Hauser & Norton, 2017; Kiatpongsan & Norton, 2014; Norton & Ariely, 2011). Instead, evidence suggests that local income inequality is associated with people's perceptions of national inequality (Minkoff & Lyons, 2019; Xu & Garand, 2010).[3]

In other words, local inequality is an important driver of what people believe about the amount of inequality in their country. This second mechanism through which local inequality matters for behaviour can be thought of as an *information* channel. While the social comparisons that are made as part of the interpersonal channel clearly confer informational content as well, this channel can be thought of as distinct as it relates to how local contexts affect aggregate perceptions, which by themselves affect behaviour.

How, then, are judgments of inequality formed? This is an important question for which there is not much evidence. Recent theoretical work by Phillips et al. (2020) suggests that physical attributes of the built environment – e.g. schools, public spaces, cars and houses – provide important informational cues. This makes sense from a behavioural science perspective. Rather than being rational agents with perfect information about aggregate inequality levels, individuals make judgments based on their more immediate surroundings and what they are able to observe (cf. also the literature on 'neighbourhood effects' mentioned above which suggests that local neighbourhoods are where knowledge about the world is accumulated (G. C. Galster, 2012)). We rely on observation of physical cues because we tend not to know what our neighbours or colleagues make – it is considered impolite to ask people about how much they earn or are worth, for instance.

Of course, other factors also affect our information gathering processes, for example Phillips et al. (2020) suggest that interpersonal comparisons and media consumption are relevant, and there are potentially other important variables, for example travel for work or time spent in other contexts, and individual differences which affect how people values and pay attention to inequality (Ho et al., 2015; Waldfogel et al., 2021).

[3] In other areas as well, individuals utilise local information when forming judgments about macro variables, e.g. national economic performance or unemployment (Ansolabehere et al., 2014; Reeves & Gimpel, 2012; Weatherford, 1983).

In short, there are two broad channels through which local inequality might affect behaviour. First, via interpersonal networks – local inequality affects the types of people that we come into contact and form friendships with. Who we encounter and socialise with affects who we compare ourselves to and therefore has important implications for our outlooks, beliefs and, ultimately, behaviour. Second, local inequality conveys information. We make judgments about aggregate inequality based on what we observe around us, in particular salient features of the physical environment (amongst other sources), and this then affects how we see the world.

1.3 An overview of the thesis

While the importance of local, contextually-relevant inequality is becoming ever clearer, 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 neighbourhood-level inequality are generally situated in the US, Canada, and other countries which gather census information on income or wealth. 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 – see M. Kuhn et al. (2020) who make this point for the US).

Against this backdrop, I aim to advance our understanding of local economic inequality in the UK, exploring its patterns, determinants, and consequences.

In Chapter 2 I examine **patterns of local economic inequality**. I do so by gathering housing value information for over 26 million UK addresses to develop a measure of local inequality in the UK. In the absence of sufficiently granular and detailed data on income or household wealth, using housing values provides reasonable estimates of local economic inequality (Alfani, 2021; Kohler et al., 2017). The size of the data allows me to reliably estimate economic inequality at a resolution that has been hitherto impossible. I then test whether housing value inequality is associated with people's perceptions of inequality across two surveys: Wave 3 of the British Election Study (BES; N = 34,808), which includes a module on perceptions of local neighbourhood inequality, and a representative sample of UK participants that I recruited via Qualtrics (N = 1,003). The findings from this work indicate that inequality based on housing values is salient – what people see around them, housing in particular, affects what they believe about economic inequality. Assessing local inequality using housing values therefore provides a geographically granular and perceptually salient measure with which to explore patterns of inequality in the UK. I conclude this chapter, by providing a contemporary picture of inequality in cities, towns, and neighbourhoods across the UK, as well as how inequality has changed over the twenty years from 1999-2019.

In Chapter 3, I contribute to our understanding of the **determinants of local economic inequality**. Recent years have seen a number of studies exploring the determinants of urban or regional inequality, with papers covering the US (Florida & Mellander, 2016; Glaeser et al., 2009), UK (N. Lee et al., 2016) and Canada (Bolton & Breau, 2012; Marchand et al., 2020). However, no study currently exists which looks at the determinants of neighbourhood-level inequality – i.e. we have limited understanding of why some local areas are more unequal than others. I find that local educational attainment is a key factor associated with greater inequality (echoing work at the urban and regional level), as is the presence of amenities – e.g. rivers, listed buildings, and parks and playgrounds.

Armed with the geographically granular and perceptually salient measure of economic inequality developed in Chapter 2, in Chapters 4 to 6 I examine the **consequences of local inequality** for a number of important individual and group behaviours.

In Chapter 4, I examine whether local inequality affects pro-social spending, providing new insight into a question that has produced conflicting findings (Côté et al., 2015; Hermanni & Tutić, 2019; Schmukle et al., 2019). Using Wave 8 of Understanding Society, a large household survey in the UK (N = 36,715), I find that local inequality interacts positively with income – higher income individuals are more generous in more unequal neighbourhoods rather than less. These findings are supported by analysis of US tax data on charitable donations and ZIP-level inequality information (N = 133,870).

In Chapter 5, in work co-authored with Thiago R. Oliveira, I explore whether variation in neighbourhood-level inequality in London affects the prevalence of police stop and search behaviour. We hypothesise that police stop and search behaviour has less to do with reducing prevalence of crime (for which the empirical evidence is scant), and more to do with social order maintenance, as criminological theories suggest (Bradford & Loader, 2016; Tiratelli et al., 2018).

We find robust evidence to support this hypothesis – inequality triggers heightened stop and search activity on the part of the police, controlling for crime rates and other important factors.

In Chapter 6, combining data on economic inequality with data on local ethnic composition from the UK census, I examine whether patterns of residential diversity and segregation affect political behaviour. Using Brexit as a case study, I find strong evidence in support of 'contact' (Allport et al., 1954) rather than 'conflict' theory (Blalock, 1967) – neighbourhood economic and social diversity reduces support for Brexit, but the opposite is true for segregation. This finding echoes other work that indicates that spatial segregation can increase anti-immigrant and populist sentiment and voting outcomes, alongside other negative outcomes (Bolt et al., 2010; Johnston et al., 2002; Kearns & Parkinson, 2001).

Viewed as a cohesive whole, the empirical contributions of this thesis demonstrate the need to and benefits of examining inequality at the local level. The measure developed in Chapter 2 enables, for the first time in the UK, the analysis of patterns of inequality within neighbourhoods. Chapter 3 provides evidence for why certain local areas are more unequal that others. Finally, the findings in Chapters 4 to 6 suggest that local economic inequality is linked to both private and public sphere behaviours, with important implications for individuals and society. As outlined in Chapter 7 – the critical discussion and conclusion – the contributions of this thesis can be built upon in future work to shed further light on important social science research questions regarding both the determinants and consequences of economic inequality.

2 Measuring local, salient inequality in the UK

Abstract: *Nascent research across social science disciplines finds that local economic inequality is an important driver of attitudes and behaviour. However, due to a lack of granular data on income and wealth in the UK, measuring local economic inequality has been impossible. I address this measurement gap by exploiting data on housing values for over 26.6 million addresses – nearly the universe of residential properties in the UK – producing a fine-grained measure of local inequality for the first time. Across two surveys, I demonstrate that housing inequality is substantively associated with perceptions of income inequality, suggesting that housing value inequality is salient to individuals. Finally, I examine patterns of inequality from the city down to the neighbourhood-level, revealing some striking facts: first, there is far larger variation in inequality at the neighbourhood-level than at the level of cities and above, pointing to varied experiences and encounters with inequality that is obscured by taking a macro focus. Second, inequality has declined at the local level on average from 1999 to 2019.*

2.1 Introduction

Economic inequality is a topic that has been extensively studied in the social sciences. Recent years have seen a renewed emphasis on measurement, with scholars increasingly taking a local-perspective, measuring inequality at relatively fine geographical resolutions (see, for example, Chetty & Hendren, 2018a), and demonstrating links between micro-manifestations of economic inequality and individual attitudes and behaviour (DeCelles & Norton, 2016; Sands, 2017; Sands & Kadt, 2020). This movement towards local inequality has happened primarily in North America, where income data is provided as part of the census (Baum-Snow & Pavan, 2013; Bolton & Breau, 2012; Florida & Mellander, 2016). Some countries, notably the UK, do not collect extensive income information from its residents, thereby making it more difficult to reliably measure economic inequality at the local 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.

This paper remedies this shortcoming by exploiting a large volume of housing value information to develop a measure of local economic inequality. The information comes from Zoopla, an online property price aggregator in the UK that provides price estimates, and the Land Registry of England and Wales, which is a ledger of realised residential property sales. Combined, I have real and estimated housing value data for over 26.6 million UK addresses. To put this number in perspective, the total number of UK addresses delivered to by the Royal Mail is around 29 million.[4] In other words, I have data for over 91% of all residential houses in the UK. The size and coverage of the data allows me to reliably estimate economic inequality at a resolution that has been hitherto impossible, providing a contemporary picture of inequality in cities, towns, and neighbourhoods across the UK, as well as changes over the the twenty year period from 1999 to 2019.

Using this data, I first test whether housing value inequality affects inequality perceptions, providing evidence as to the salience of local inequality derived from housing data. I test this relationship using two surveys: Wave 3 of the British Election Study (BES), which includes a module on perceptions of local neighbourhood income inequality, and a representative sample of UK participants (age, gender, and income) that I recruited via Qualtrics (N = 1,003). I find that housing value inequality is indeed associated with perceptions, even after controlling for a number of known correlates, for example political orientation and education. 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.

The Qualtrics survey also includes a free text box for respondents to explain how they formed their perceptions. Quantitative text analysis reveals that a key feature for respondents' assessments of local inequality is the quality and discrepancy of local housing stock. Altogether these 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. This is the first empirical evidence, as far as I am aware, of a relationship between features of the built environment and perceptions of inequality.

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

This finding also overcomes a key weakness of using housing data to measure inequality. Housing, although closely linked with wealth in general (M. Kuhn et al., 2020), does not necessarily correspond to traditional measures of economic resources here because the data does not distinguish owners from renters. Thus housing value inequality might not correspond with actual levels of income or wealth inequality. Instead, inequality of housing values should be thought of in perceptual terms – it measures *salient* economic inequality rather than *objective* economic inequality. This is important because a growing body of work demonstrates that perceptions of inequality, rather than actual levels, are important drivers of attitudes and behaviour (Cruces et al., 2013; Hauser & Norton, 2017; A. Kuhn, 2019).

In the second part of this paper, I describe patterns of local inequality in the UK. I adopt a multi-scalar approach (Cavanaugh & Breau, 2018) to do so, going from UK cities down to highly disaggregated neighbourhoods. All 77 cities in the UK (defined as having a population of at least 100k residents in the last census) are included in the analysis, as are all 519 towns (defined as having a population of at least 10k but less than 100k). Finally, given the immense size of the data, I explore neighbourhood-level inequality for the whole of the UK. For neighbourhoods, I take the Lower Super Output Area (LSOA) or the nearest equivalent in Scotland and Northern Ireland (Data Zones and Super Output Areas respectively). LSOAs are census boundaries standardised in terms of population size, containing an average of 1,400 residents. The Zoopla data provides an average of 539 housing values per LSOA for 2019. The Land Registry provides coverage of 70.15% of LSOAs in England and Wales for the years 1999 and 2019.[5] I also examine alternative definitions of 'neighbourhood' to mitigate issues arising from the Modifiable Areal Unit Problem (see, for example, Openshaw, 1984), i.e. that measures of local inequality might be sensitive to choices around aggregation.

The data reveals substantial variation in neighbourhood inequality. Indeed, inequality in the UK is far more dispersed within cities than between them. For example, neighbourhood inequality in London ranges from 0.042 to 0.649, which is far larger than the difference between London as a whole, the most unequal city in the UK, and Luton, the most equal (0.152). More generally, urban areas in the UK tend to exhibit extremes – neighbourhoods of extremely high and

[5] I drop all areas for which there is less than 50 values, leaving a total of 41,742 LSOAs (or 98% of the total number of LSOAs in the UK. Most of Northern Ireland is dropped due to 94.8% of the Data Zones having less than 50 observations.

extremely low levels of inequality, sometimes side-by-side. This suggests that the experience of inequality within urban settings varies substantially, with concomitant consequences for people's attitudes and behaviour. The data also reveals that urban and neighbourhood inequality has declined on average over the last couple decades in England and Wales. However, there is substantial variation in this change – there are pockets of substantial increases in inequality, notably in Central London, Greater Manchester and the North East.

In what follows, Section 2 presents the background to this paper, Section 3 details the data on local inequality in the UK, Section 4 explores the link between these measures and people's perceptions of inequality, Section 5 provides an anatomy of inequality in the UK, and Section 6 concludes by discussing the paper's overall contributions and limitations.

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

2.2 Background

This paper builds on existing literature which helps motivate the use of housing values to estimate local inequality and emphasises the importance of perceptually salient measures of inequality.

2.2.1 Measuring inequality using housing values

As residential housing assets make up a large majority – approximately 60% – of overall UK household wealth[6], inequality based on housing values can best be thought of as a measure of wealth inequality (see also, 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).

[6] 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

Moreover, 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 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). Taken together, in the absence of sufficiently granular, detailed data on income or household wealth, using housing values provides reasonable estimates of local economic inequality.

2.2.2 Perceptions of inequality

A burgeoning academic literature stresses the importance of perceptions of inequality. A number of studies demonstrate 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). Moreover, there is an emerging consensus among scholars across disciplines that perceptions of inequality are an important factor shaping attitudes and behaviour (Ansell & Cansunar, 2020; Nishi et al., 2015; B. K. Payne et al., 2017; Trump, 2016), 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).

How do individuals form these perceptions? Recent theoretical work by Phillips et al. (2020) suggests three different types of informational cues are important: 1) interpersonal comparisons (see also Kraus et al. (2017), and for a more general take G. C. Galster (2012)); 2) media attention; and 3) 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, for example, Dawtry et al., 2015; Diermeier et al., 2017), as far as I am aware there has not yet been any empirical work that examines whether physical attributes affect inequality perceptions. I provide such evidence in this paper.

2.3 Data on local inequality in the UK

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 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.[7]

Data from the Land Registry consists of realised sale prices of residential housing in England and Wales beginning in 1995. This allows me to explore how local inequality has changed over the last two decades. 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.

[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.

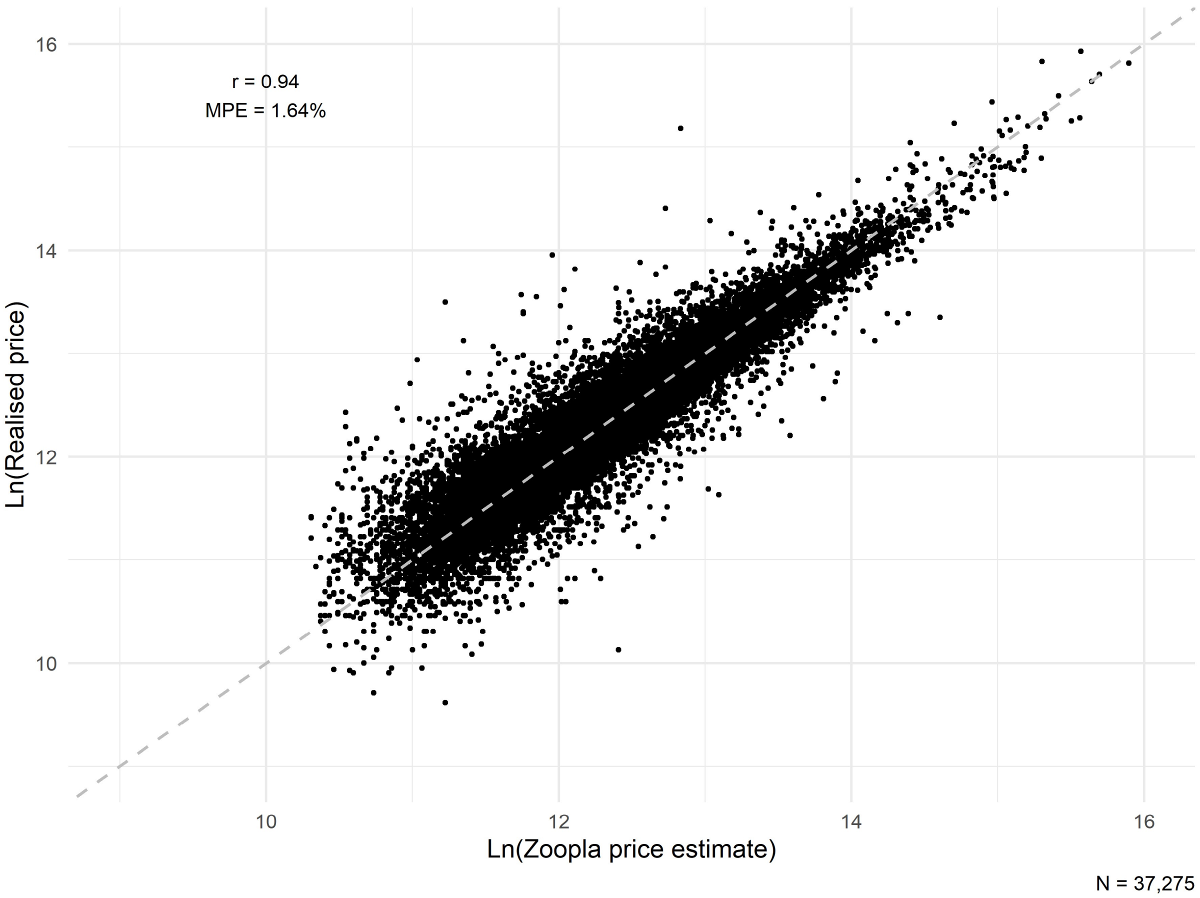
I take the Gini coefficient as the preferred measure of inequality. This can be calculated for a given area as the mean absolute difference between each pair of observations divided by two times the mean housing value, or formally:

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

To see how the Gini compares with alternative measures of inequality, Figure A.1 in the Annex provides the correlation matrix for the Gini and a number of other measures at different levels of geographical aggregation, the LSOA and towns and city-level. In particular, I include decile ratios (90:10, 50:10, 90:50), top 1% concentration, and the coefficient of variation. The Gini is highly correlated with other measures, for example the correlation coefficient is 0.66 and 0.68 between the Gini and top 1% measures at the LSOA and city levels respectively.

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 0.94, and the mean percentage error is 1.64% – see Figure 1. Moreover, the Gini coefficients from Zoopla and the Land Registry are very highly correlated at the LSOA-level (r = 0.9), 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.

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. This therefore suggests that housing value inequality does not correspond with traditional objective inequality measures based on income or wealth. While I stress here the importance of a perceptually salient measure of inequality rather than one that is solely objective, I nevertheless address this concern by showing that, for larger geographical levels where sufficient data exists to estimate inequality (i.e. only as fine as the Parliamentary Constituency level), housing value inequality is strongly correlated with income inequality. I also estimate inequality using banded income estimates at the LSOA-level provided by the ONS for 2018. Even with this rather coarse income inequality measure, I find a strong correlation with inequality derived from housing values. See these results in Table A.1 and Table A.2 in the Annex.

2.4 Salience of housing value inequality

Given the importance of perceptions of inequality for attitudes and behaviour (see, for example, Cruces et al., 2013), and in order to validate the salience of the measures detailed above, I turn to assessing whether individual perceptions of local inequality are linked to housing value inequality.

I investigate this question using two surveys. First, I exploit Wave 3 of the British Election Study (BES) 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, 2019). Wave 3 of BES provides a large sample size (N = 12,193) and geographical markers at the Middle Super Output Area (MSOA), which are comprised of LSOAs and have an average population 7,787. However, BES respondents volunteer to participate and therefore the panel is non-representative of the UK population. Moreover, known correlates of inequality perceptions, notably Social Dominance Orientation (SDO, Ho et al. (2015)) and Personal Relative Deprivation (PRD; Callan et al. (2011)), are missing. Data for BES Wave 3 was collected in 2015, so I use the measure of inequality for 2014 based on the Land Registry data.[10]

To overcome the limitations of BES, and also to ensure the findings are robust, I recruited a panel of respondents from Qualtrics (N = 1,003) in October-November 2019 that is representative of the UK population on age, gender and income. To achieve representativeness on income, I use percentile data provided by HMRC's Survey of Personal Incomes. I asked 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". I ask participants to provide postcode information, and so I am able to link responses to LSOAs as well as MSOAs. 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 LSOA and MSOA boundaries adequately proxy for respondent

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[10] I check whether using the inequality measure based on the Zoopla data affects the findings (unreported) – it does not.

neighbourhood boundaries. 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 the US are more closely aligned with subjective perceptions of local characteristics (Velez & Wong, 2017).

Immediately after their numerical assessments, I provide respondents with a free-text box and ask them to explain why they responded in the way they did, i.e I obtain descriptions of what information individuals use in assessing local inequality. I then ask a series of further questions designed to serve as individual-level control variables: in particular, I ascertain SDO using the eight-item scale developed by Ho et al. (2015), and PRD using the five-item scale from Callan et al. (2011). I also ascertain political orientation (using an 11-point left-right scale), and demographic information (age, gender, education, and income) to include as controls.

2.4.1 Multivariate analysis

To analyse the relationship between housing value inequality and perceptions of inequality, I specify the following random intercept model to examine associations between housing value inequality and subjective assessments:

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

where y_{ij} is the subjective assessments of inequality for individual i in area j, α is the intercept, X_{ij} is the vector of individual-level controls, Z_j is the vector of area-level controls (average property value and population density), 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 contextual inequality on subjective perceptions. For area level controls, I include the average property value and population density. For individual-level controls, I includes age, gender, education and political orientation. Additionally for the Qualtrics survey I include SDO and PRD.

Table 1 provides results for the BES study. Column 1 is the Gini without area or individual-level control variables, and Column 2 includes 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 0.077 of a standard deviation respectively for Column 1 and 2.

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

	Dependent variable:	
	Perceived local inequality	
	(1)	(2)
Gini	0.108^{***}	0.077^{***}
	(0.010)	(0.012)
Avg house value		0.122^{***}
		(0.012)
Density		-0.016
		(0.011)
Income middle		0.013
		(0.024)
Income rich		0.032
		(0.032)
Left-right		-0.155^{***}
		(0.011)
Tertiary		0.110^{***}
		(0.022)
Female		0.011
		(0.021)
Age 55+		0.051^{*}
		(0.029)
Age 35-55		0.045
		(0.030)
Constant	-0.002	-0.093^{***}
	(0.009)	(0.033)
Controls	No	Yes
Observations	12,192	9,178
Log Likelihood	-17,233.300	-12,860.170
Akaike Inf. Crit.	34,474.600	25,746.350
Bayesian Inf. Crit.	34,504.240	25,838.970
Note:	*p<0.1; **p<0.05; ***p<0.01	
	The table provides estimates for the relationship between local inequality and perceived local income inequality	
	All continuous variables are scaled, and standard errors in parentheses	

Table 2 provides the results for the Qualtrics survey. Columns 1 and 2 are for LSOA-level housing value inequality with and without the additional covariates (SDO and PRD), and Columns 3 and 4 are for the MSOA-level. I find the coefficient on the Gini to be significant and substantive in size for each model. Housing value inequality, at both the LSOA and MSOA level, is associated with perceptions of local inequality.[11] The standardised coefficient estimates are similar in size as that found in analysis of the BES survey.

Moreover, the inclusion of the additional controls does not 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.

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[11] In unreported findings, I find that more aggregated measures of inequality are not associated with perceptions of UK-level inequality, a finding that is in line with research (e.g. Norton & Ariely, 2011) which finds that individual assessments of national-level inequality are very different from actual levels. On the other hand, city-level inequality is associate with perceptions of national-level inequality, which also conforms with other findings (e.g. Ansolabehere et al., 2014; Minkoff & Lyons, 2019).

Table 2: Perceptions of local income inequality – Qualtrics survey

	Perceived local income inequality			
	LSOA	LSOA	LSOA	MSOA
	(1)	(2)	(3)	(4)
Gini	0.077**	0.085**	0.092**	0.092***
	(0.036)	(0.036)	(0.036)	(0.035)
Avg house value	0.016	0.024	0.027	0.033
	(0.035)	(0.034)	(0.034)	(0.034)
Density	0.044*	0.042*	0.043*	0.037
	(0.024)	(0.024)	(0.025)	(0.024)
Income middle	-0.041	-0.029	-0.020	-0.004
	(0.089)	(0.088)	(0.089)	(0.088)
Income rich	0.023	0.084	0.006	0.065
	(0.110)	(0.109)	(0.109)	(0.109)
Left-right	-0.093***	-0.073**	-0.100***	-0.079**
	(0.032)	(0.034)	(0.031)	(0.034)
Tertiary	0.031	0.055	0.027	0.050
	(0.067)	(0.066)	(0.066)	(0.065)
Female	0.055	0.050	0.068	0.062
	(0.070)	(0.070)	(0.070)	(0.069)
Age 55+	0.206***	0.212***	0.216***	0.228***
	(0.077)	(0.076)	(0.076)	(0.076)
Age 35-55	0.100	0.191**	0.096	0.182**
	(0.090)	(0.091)	(0.090)	(0.091)
SDO		0.042		0.043
		(0.035)		(0.034)
PRD		-0.156***		-0.143***
		(0.032)		(0.032)
Constant	-0.291**	-0.328***	-0.286**	-0.312***
	(0.119)	(0.118)	(0.113)	(0.112)
Controls	No	Yes	Yes	No
Observations	999	999	1,003	1,003
Log Likelihood	-1,420.085	-1,412.730	-1,425.736	-1,419.988
Akaike Inf. Crit.	2,866.169	2,855.461	2,877.472	2,869.976
Bayesian Inf. Crit.	2,929.957	2,929.062	2,941.312	2,943.638

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

The table provides estimates for the relationship between local inequality and perceived local income inequality

All continuous variables are scaled, and standard errors in parentheses

2.4.2 Text analysis

These findings point to the relevance of housing value discrepancies for judgments about local inequality. But what environmental cues do people use when making assessments about economic inequality? Surprisingly, and despite a large volume of studies examining perceptions of inequality, this basic question has not been posed. I suppose that, because incomes are generally unobserved, people make inference about their neighbours' income based on what they can observe, in particular the size and quality of their house (as well the car they drive and their visible consumption habits, such as the clothes they wear). I therefore provide the space for respondents to explain why they came to the judgments they did about local inequality in order to remedy this shortcoming and provide greater understanding.

I first conduct some basic quantitative analysis of the text responses by creating dictionaries for housing-related and income-related words. For housing, I include: 'hous*', 'home*', 'propert*', 'rent*', 'flat*', 'estate*', 'council*'. For income, I include: 'incom*', 'earn*', 'wage*', 'salar*', 'job*', 'unemp*'.[12] Table 3 provides the raw count for the housing and income dictionaries by text response. I find that housing-related words are used by participants nearly twice as frequently as income-related words when participants explain why they answered the numerical question on perceptions as they did.

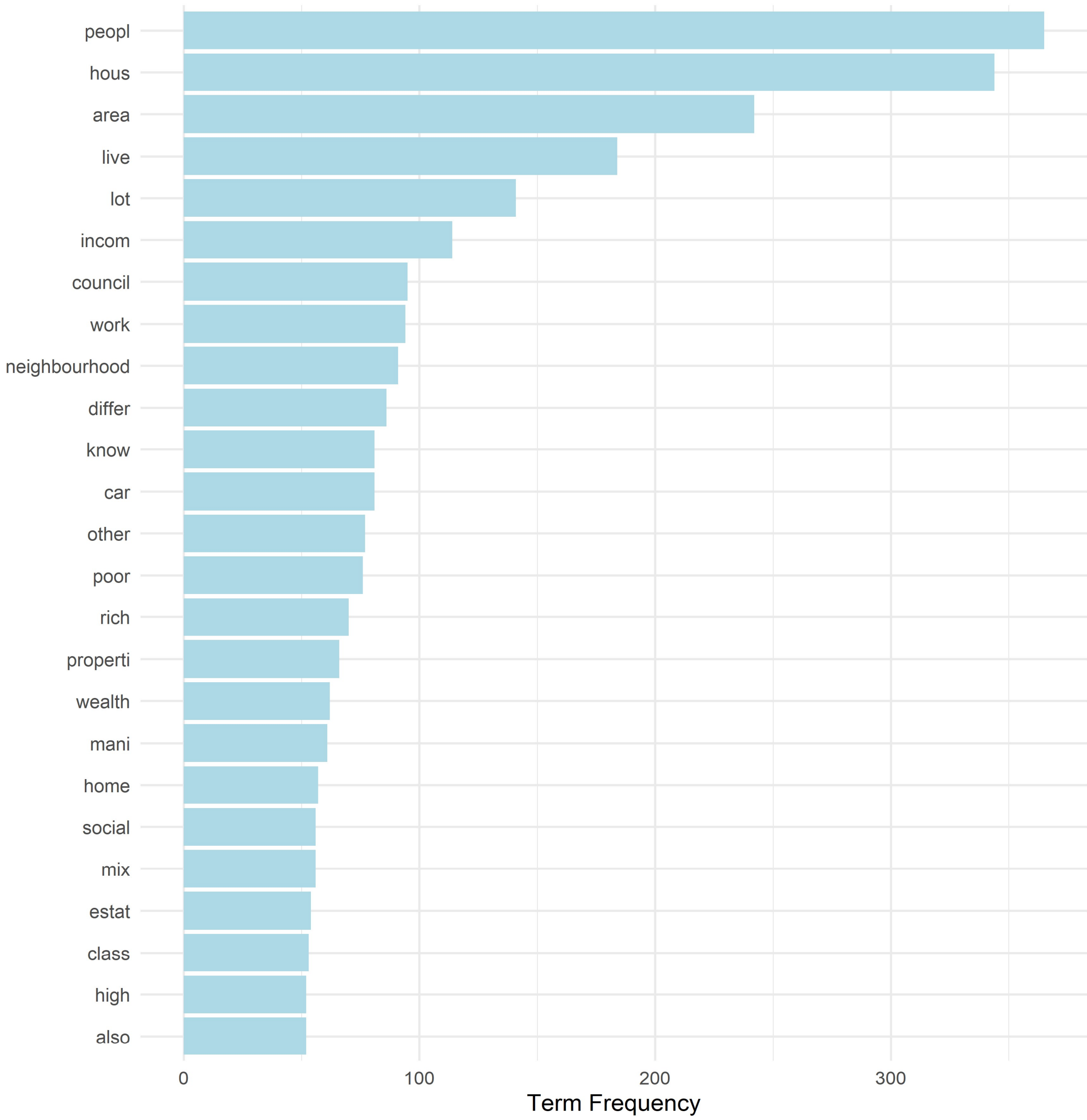
Figure 2 provides a frequency chart for the most utilised stemmed words. Peopl* is the most utilised term, providing support for the interpersonal channel being important for affecting people's perceptions of local inequality (Phillips et al., 2020). Hous* is the second most frequently used stem, only slightly behind peopl*. This provides additional support for the relevance of housing discrepancies in local areas for people's perceptions of inequality.

Table 3: Raw counts for housing and income dictionaries

	Housing related	Income related
Count	475	287

[12] The '*' denotes all words that grow from the stem of the word. So for hous* we have: 'housing', 'house', 'houses', etc.

Figure 2: Frequency charts for local inequality textual responses



Note: The figure shows stemmed term frequencies for the textual responses asking respondents to describe how they assessed inequality in their local area (N = 1,003).

However, the raw counts and frequencies do not reveal much about the context and semantic use of the word in question. In other words, we might not know whether a housing or income-related word denotes the relevance of that concept in making inequality assessments or the reverse. For example, a participant might mention 'income' in order to indicate that it does *not* form part of their assessment. To get a clearer understanding of what information people are using, I examine relevant extracts where either income or housing related words are being used. Some indicative examples include:

> "There's a huge mix of council estates and multimillion pound houses next door to eachother."
>
> "There's areas with poor people and government housing and areas with fancy big houses."
>
> "There are obviously some people who have a higher income as can be seen by the cars they drive and things like that."
>
> "I don't really know about other people's income and wealth so can only really base it on state of properties."

These extracts suggest that housing is a crucial feature for people in making their assessments. Some respondents are explicit about how this works: they can only infer about other people's income, and therefore income inequality, based on the things that they can directly observe. In other words, the local housing stock, rather than income, is salient for individuals when judging the level of local income inequality.

2.5 An anatomy of local economic inequality in the UK

Having developed the measures of local inequality based on housing value data and produced evidence as to the salient nature of these measures, I now turn to describing patterns of local inequality in the UK. I first focus on urban areas in the UK – i.e. inequality at the level of towns and cities. I combine all built-up areas[13] in England and Wales with Settlements[14] in Scotland and Northern Ireland that contain at least 10k residents in the 2011 census. Given the size of the data on housing values, I cover all towns and cities in the UK (N = 596), thereby expanding on the pioneering descriptive analysis of sub-national inequality in the UK by N. Lee et al. (2016), who use data on employee wages from the Annual Survey of Hours and Earnings (ASHE; ONS (2019)) to estimate inequality for 60 British cities.

Table 4 and Table 5 provides a ranking for the ten most equal and unequal areas separately for cities and towns. Towns as defined as areas with at least 10k residents but less than 100k (N = 519), and cities are areas with 100k or more residents (N = 77). First, looking at cities, we see that Greater London is the most unequal with a Gini coefficient of 0.356, followed by Belfast

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[13] These are geographical areas defined by the ONS and UK Ordnance Survey. Details available here: https://www.nomisweb.co.uk/articles/ref/builtupareas_userguidance.pdf.

[14] These are built-up area equivalents defined by the governments of Scotland and Northern Ireland respectively, and can be accessed here for NI: https://www.nisra.gov.uk/support/geography/urban-rural-classification, and here for Scotland: https://www.nrscotland.gov.uk/statistics-and-data/statistics/statistics-by-theme/population/population-estimates/settlements-and-localities.

and three Scottish cities, Glasgow, Edinburgh and Aberdeen. The top four most unequal cities vary substantially in terms of median house price, which can be considered a proxy of median wealth, suggesting that inequality is not simply a product of overall economic success. Indeed, Belfast, Greater Glasgow, and Burnley (the 7th most unequal city) are relatively poor urban areas as well as being unequal. Looking at the most equal cities, Luton ranks last unequal with a Gini coefficient that is 57.3% the size of London's. These rankings and absolute figures generally align with those of N. Lee et al. (2016), although the definition of city is different and I am using housing values rather than employee wages to estimate inequality.

Turning to UK towns, Cobham (Elmbridge) is the most unequal, and indeed is 17.4% more unequal than London, whereas the least unequal town, New Addington, is about two times more equal than Luton, the most equal city. In general, the range of the Gini is far greater amongst towns than cities (0.309 versus 0.152).

Next, turning to the neighbourhood-level, Figure 3 maps LSOA-level inequality in the UK. The neighbourhood Gini ranges from 0.018 to 0.649, with a mean value of 0.195 and standard deviation equal to 0.066. We can see from the map (Panel A) that the major cities and South East of England tend to have a mix of relatively equal and unequal LSOAs, whereas rural areas tend to display an average level of housing value inequality. To help see this, Panel B pulls out London. The UK capital contains the most unequal LSOAs in the country, with areas in the West-end and South-West of the city being particularly unequal.

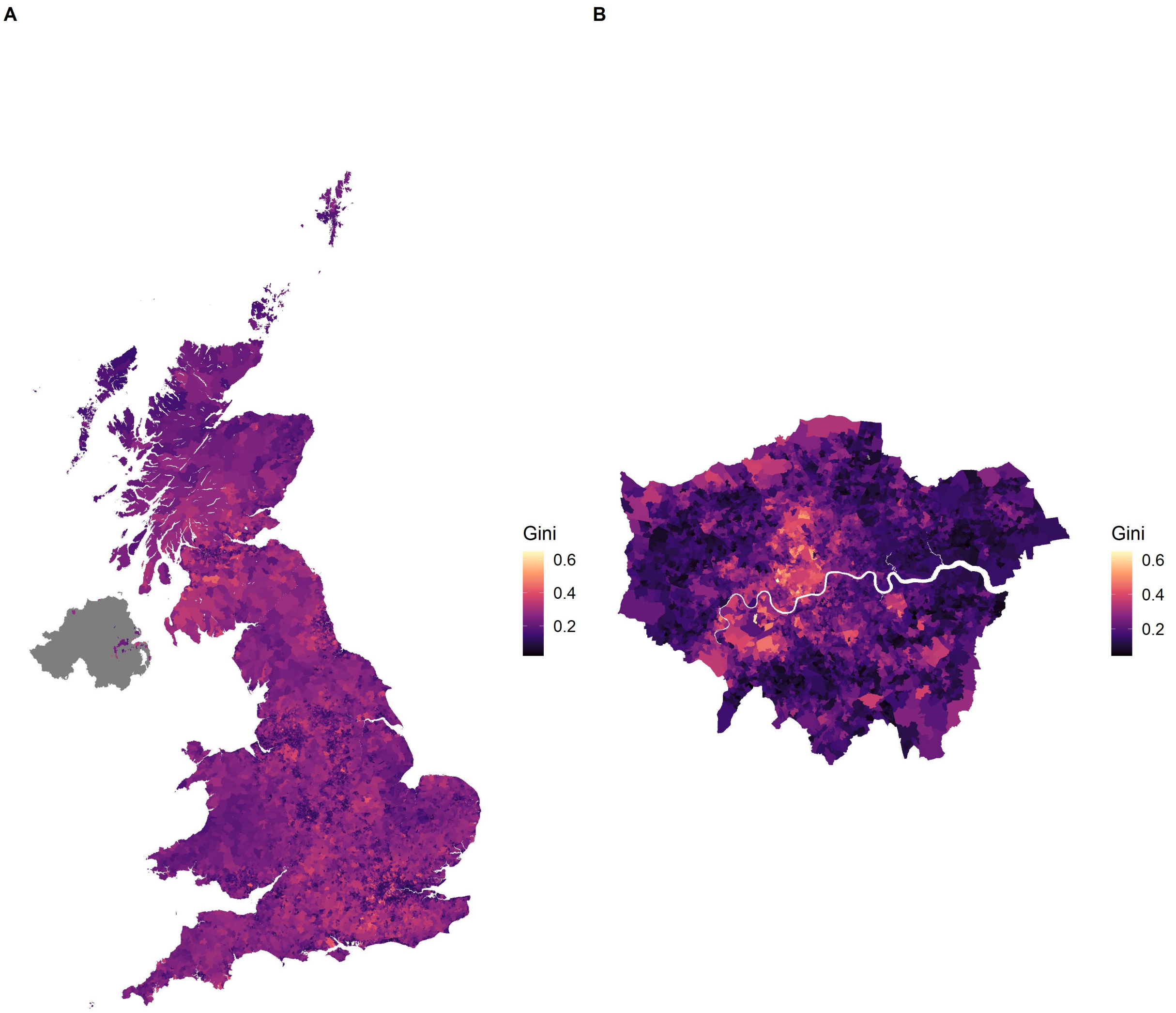
Table 4: Ranking of most and least unequal cities in the UK, 2019

City	Population	Gini	Median	Top1	9:1	9:5	5:1
Rank: Top 10							
Greater London	9,791,957	0.356	432,000	8.260	3.908	2.262	1.728
Belfast	341,035	0.355	148,000	6.657	4.300	2.324	1.850
Greater Glasgow	968,033	0.351	130,000	5.321	4.769	2.385	2.000
Edinburgh	488,095	0.339	226,000	5.306	4.120	2.279	1.808
Aberdeen	213,725	0.331	152,000	4.869	4.092	2.342	1.747
Greater Manchester	2,551,155	0.327	149,000	5.766	3.890	2.141	1.817
Burnley	151,732	0.326	87,000	4.707	4.239	2.241	1.891
Falkirk	103,003	0.321	104,000	4.121	4.276	2.385	1.793
Sheffield	683,577	0.316	136,000	4.908	3.844	2.176	1.766
Accrington/Rossendale	126,031	0.316	102,000	4.672	3.930	2.196	1.789
Rank: Bottom 10							
Crawley	181,620	0.231	298,000	3.737	2.677	1.752	1.528
Chelmsford	110,655	0.230	332,000	3.352	2.854	1.711	1.668
Worcester	102,290	0.229	202,000	3.387	2.732	1.718	1.591
Gloucester	151,914	0.229	200,000	3.247	2.814	1.660	1.695
York	154,123	0.227	214,000	3.857	2.549	1.692	1.507
Swindon	187,059	0.227	199,000	3.195	2.766	1.696	1.631
Lincoln	114,842	0.223	155,000	3.435	2.569	1.690	1.520
Basingstoke	107,996	0.221	254,000	3.387	2.593	1.756	1.477
Medway Towns	244,765	0.220	231,000	3.110	2.710	1.701	1.593
Luton	259,057	0.204	234,000	2.967	2.574	1.551	1.660

Table 5: Ranking of most and least unequal towns in the UK, 2019

Town	Population	Gini	Median	Top1	9:1	9:5	5:1
Rank: Top 10							
Cobham (Elmbridge)	17,930	0.418	885,500	5.268	7.318	2.752	2.659
Haslemere	14,291	0.372	434,000	5.149	5.581	2.675	2.087
Sevenoaks	30,692	0.372	498,000	4.851	4.959	2.659	1.865
Hamilton	82,220	0.366	101,000	5.730	5.078	2.564	1.980
Beaconsfield	13,523	0.362	784,500	4.607	5.584	2.292	2.436
Hawick	16,855	0.349	89,000	5.873	4.462	2.607	1.712
Knutsford	13,191	0.348	314,000	6.334	4.396	2.156	2.039
Macclesfield	63,177	0.347	198,000	7.284	3.965	2.303	1.722
Cumbernauld	54,773	0.345	99,000	4.263	5.180	2.616	1.980
Cookstown	17,339	0.341	130,000	6.232	4.073	2.074	1.964
Rank: Bottom 10							
Haverhill	27,041	0.176	206,000	2.530	2.108	1.617	1.304
Maghull	26,752	0.176	202,000	2.969	2.034	1.460	1.393
Stanford-Le-Hope	28,971	0.169	294,000	2.737	2.243	1.442	1.556
Amesbury	10,724	0.169	244,000	3.079	2.040	1.455	1.402
Didcot	29,073	0.164	295,000	3.041	2.043	1.447	1.411
Peacehaven	18,731	0.158	291,000	2.665	2.151	1.323	1.626
Carterton	15,769	0.156	264,000	2.175	2.176	1.451	1.500
Canvey Island	38,170	0.151	255,000	2.303	1.907	1.443	1.321
Sheerness	11,938	0.149	169,000	2.466	2.009	1.308	1.536
New Addington	22,280	0.109	287,000	1.826	1.678	1.169	1.435

Figure 3: Map of LSOA-level inequality in the UK

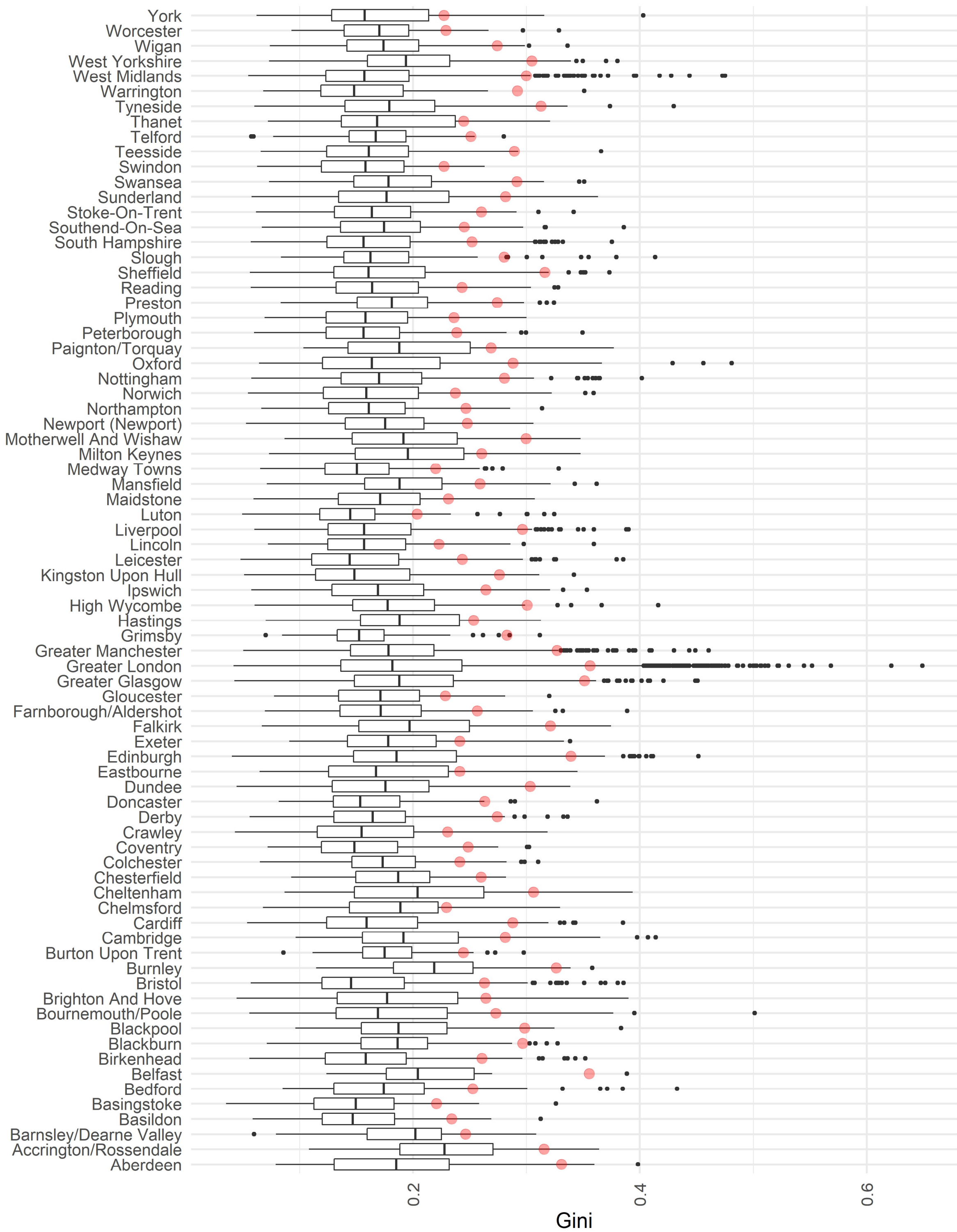


Note: Panel A provides shows neighbourhood (LSOA)-level Gini coefficients for the UK, and Panel B pulls out London. All estimates based on house price data from Zoopla for 2019.

More generally, a neighbourhood-level view shows that urban areas contain both highly equal and highly unequal neighbourhoods, oftentimes existing side-by-side. This highlights that experiences of economic inequality, and thus also the potential consequences of inequality, are likely to vary substantially within cities. Taking an aggregated perspective obscures the wide variation that exists when taking a more local focus. Indeed, the difference between the most unequal and equal neighbourhood in London in terms of the Gini coefficient (0.607) 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 4 provides the distribution of neighbourhood-level inequality for each city in the UK. This figure reveals an interesting fact – inequality at the city-level is at the higher end of the neighbourhood range, and in all cases above the 75th percentile. What explains this? One reason might be that cities exhibit economic segregation by neighbourhood (Cheshire, 2007; Daniel Dorling et al., 2007; Meen & Gibb, 2005). In other words, neighbourhoods are more frequently equal and rich or equal and poor than they are unequal. Figure A.2 visualises this by mapping the bivariate relationship between median housing value and inequality for the UK.

Figure 4: Neighbourhood inequality by city in the UK, 2019



Note: The figure shows inequality at the city-level (red dot) and within-city neighbourhood inequality (box plot).

Next, I use the Land Registry data to describe changes in local inequality over time. Interestingly, inequality has reduced on average for cities, towns and LSOAs in England and Wales over the twenty year period from 1999 to 2019 (M = -0.025, -0.023, and -0.018 respectively, SD = 0.022, 0.024, and 0.044). Table 6 and Table 7 rank changes in inequality for the top and bottom 10 cities and towns respectively by the largest absolute change in Gini.

First, looking at the rankings for cities – the biggest increase in the Gini has been in Oxford, Blackpool, Cheltenham and Cambridge. Of these four cities, Blackpool stands out as being relatively poorer and is considered to be in decline. Oxford, Cambridge, and Cheltenham are, on the other hand, prosperous places that have been growing rapidly. This demonstrates that inequality can increase even if the overall economy is suffering in relative terms. Table 6 shows that Blackpool has seen a relatively larger increase in bottom end inequality (measured by the change in the 50:10 ratio).

Figure 5 shows the change in the Gini coefficient for the MSOA-level. I map this spatial level due to a high percentage of missing values at the LSOA-level – 14% – when dropping areas with less than 50 observations in either 1999 or 2019. Panel A shows the spatial distribution of change for England and Wales, and Panel B pulls out London. The maps demonstrate that most MSOAs in England and Wales have seen a reduction in inequality (M = -0.022), oftentimes substantial. However, as the map of London demonstrates, change is not randomly 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.

How do changes in local inequality compare with more aggregate-level changes? To answer this, Figure 6 plots the change in UK inequality over the two decades using the housing value data. The time series shows that UK inequality has been static overall with a slight dip around the global financial crisis of 2008-9. The UK-level housing value inequality trend broadly aligns with that of other measures. For example, data from the World Inequality Database (WID) suggests that pre and post-tax income inequality has been static over the same period (see the data provided online here: https://wid.world/). Regarding aggregate wealth inequality, reliable data is hard to come by, with estimates based on household surveys generally requiring a lot of assumptions (Advani, Bangham, et al., 2020; Alvaredo et al., 2016) or generally spotty and incomplete. Nevertheless, data from the WID, shows inequality of personal net wealth to also be generally flat between 1999-2019.

Table 6: Rank of cities by change in inequality, England & Wales (1999 to 2019)

City	Gini change	Gini change (%)	Top 1% change	9:1 change	9:5 change	5:1 change
Rank: Top 10						
Oxford	0.036	13.086	0.017	0.237	0.048	0.080
Blackpool	0.014	4.937	0.004	0.368	0.053	0.142
Cheltenham	0.013	4.168	0.007	0.159	-0.025	0.095
Cambridge	0.012	4.358	0.001	0.170	0.008	0.079
Sheffield	0.011	3.736	-0.002	0.374	0.126	0.068
Liverpool	0.011	3.724	0.002	-0.099	0.101	-0.165
Cardiff	0.005	1.957	-0.002	0.144	0.110	-0.025
Teesside	0.004	1.323	-0.003	0.097	0.058	-0.015
Grimsby	0.004	1.354	-0.003	0.254	-0.097	0.249
Exeter	0.002	0.815	0.002	-0.006	-0.051	0.043
Rank: Bottom 10						
Colchester	-0.048	-17.085	-0.011	-0.468	-0.388	0.105
Leicester	-0.049	-17.399	-0.010	-0.698	-0.189	-0.207
High Wycombe	-0.051	-15.596	-0.007	-0.676	-0.384	0.005
Blackburn	-0.053	-15.326	-0.010	-1.314	-0.250	-0.373
Telford	-0.054	-18.662	-0.005	-0.889	-0.289	-0.192
Hastings	-0.054	-17.039	-0.008	-1.257	-0.266	-0.363
Coventry	-0.058	-19.950	-0.010	-0.858	-0.202	-0.284
Medway Towns	-0.059	-22.319	-0.006	-0.780	-0.339	-0.138
Slough	-0.061	-18.456	-0.022	-0.358	-0.312	0.081
Basildon	-0.067	-23.794	-0.005	-1.156	-0.343	-0.313

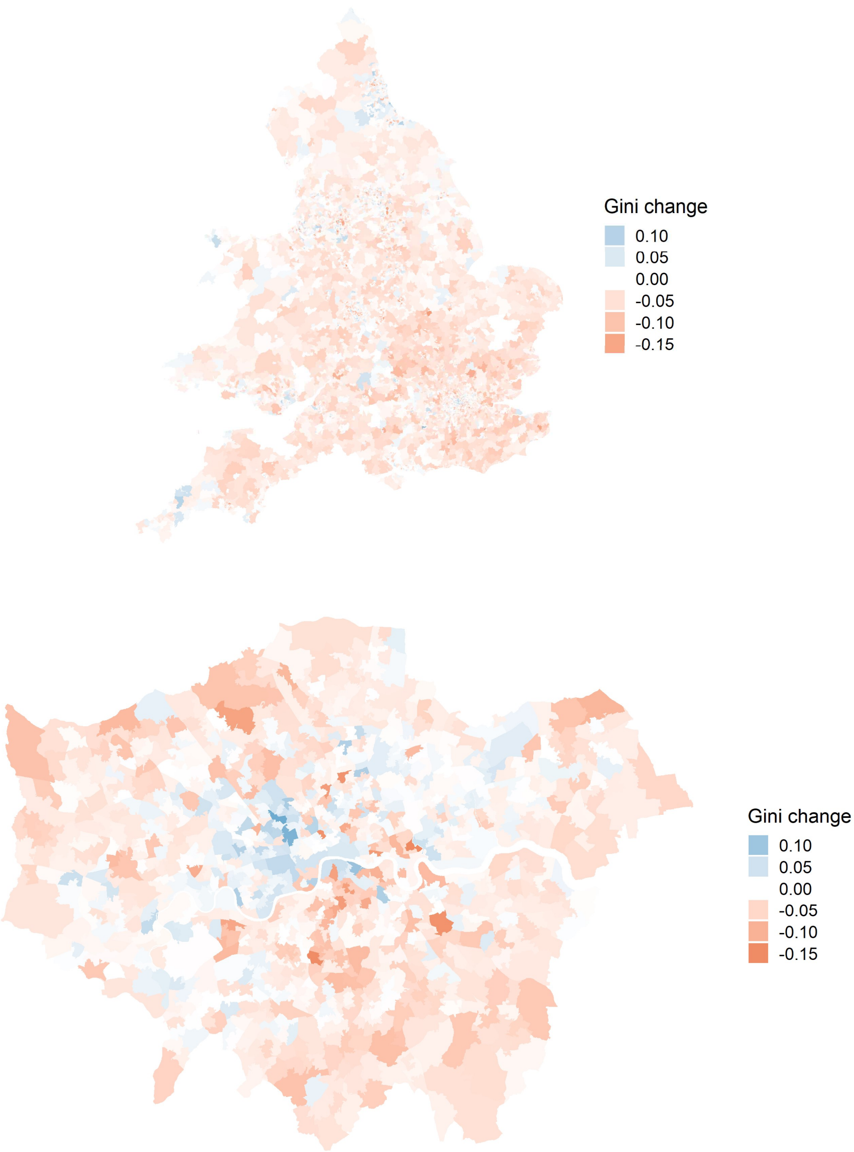
Table 7: Rank of towns by change in inequality, England & Wales (1999 to 2019)

Town	Gini change	Gini change (%)	Top 1% change	9:1 change	9:5 change	5:1 change
Rank: Top 10						
Shildon	0.080	29.964	0.000	1.376	0.743	-0.042
Ponteland	0.047	18.799	0.007	0.530	0.190	0.068
Peterlee	0.044	14.110	0.002	1.997	0.124	0.752
Stamford	0.037	15.067	0.005	0.412	0.120	0.121
Llantwit Major	0.036	15.839	0.002	0.680	0.076	0.318
Spennymoor	0.035	13.657	-0.007	1.507	-0.008	0.867
Bishop Auckland	0.033	11.300	-0.002	1.202	-0.095	0.738
Berwick-Upon-Tweed	0.033	12.204	0.001	0.358	0.267	-0.041
Wells	0.032	14.101	-0.002	0.529	0.156	0.158
Knutsford	0.030	9.096	0.016	0.277	-0.129	0.243
Rank: Bottom 10						
Rushden	-0.073	-25.491	-0.010	-1.162	-0.360	-0.301
Market Warsop	-0.073	-24.530	-0.012	-1.631	-0.190	-0.736
Corby	-0.074	-27.319	-0.024	-0.902	-0.257	-0.277
Newhaven	-0.074	-30.931	-0.009	-0.832	-0.245	-0.297
Shirebrook	-0.082	-30.748	0.005	-2.153	-0.376	-0.856
Grays	-0.082	-29.252	-0.008	-1.316	-0.454	-0.275
Swanley	-0.082	-31.787	-0.014	-0.644	-0.355	-0.053
Wellingborough	-0.086	-29.313	-0.006	-1.491	-0.420	-0.424
South Ockendon	-0.107	-39.151	-0.011	-1.617	-0.517	-0.404
King's Lynn	-0.107	-32.322	-0.094	-0.409	-0.114	-0.127

Figure 5: Change in MSOA inequality, England & Wales (1999 to 2019)

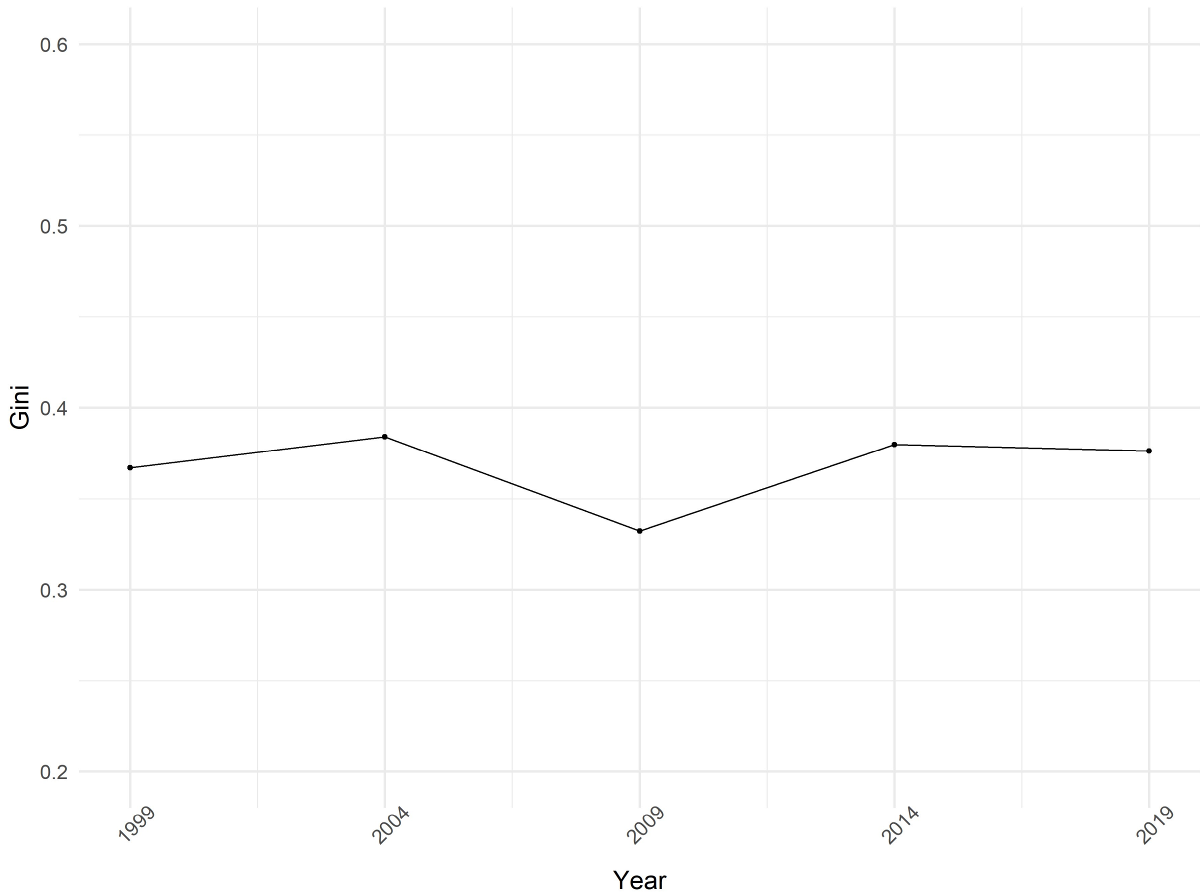
A

B



Note: The figure shows change in the absolute value of the Gini coefficient of housing values 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).

Figure 6: Change in UK inequality, 1999-2019



Note: The figure shows UK-level housing value inequality from 1999 to 2019.

2.6 Discussion and conclusion

In this paper, I provide a novel and unique measure of local economic inequality in the UK. 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 a hyper-local level for the first time. Clearly, estimates of inequality based on housing values do not correspond with more traditional approaches to measuring inequality, e.g. via surveys or administrative data providing information on actual income and wealth. For one, 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. I test the hypothesis that individuals make inferences about the level of actual income inequality partly by what they observe around them in the form of housing, rather than by having actual information on incomes.

I test whether local housing value inequality is associated with perceptions of income inequality using 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. This conclusion is buttressed by textual responses – local housing discrepancies are frequently mentioned as being a key feature used by individuals to estimate neighbourhood inequality, indeed more so than incomes. 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' – but also because it represents the first evidence of the importance of features of the built environment feeding into perceptions of economic inequality.

The measures of local inequality allow me to describe neighbourhood-level variation, as well as that in towns and cities across the UK, providing the first multi-scalar exploration of the anatomy of local inequality in the UK of its kind. Rather than focus on one geographic level, I explicitly compare results for perceptions and patterns at different geographical scales and alternative ways of defining 'local'. This approach defends against issues arising from the Modifiable Areal Unit Problem (Openshaw, 1984), as well as providing a more nuanced understanding of the geography of inequality levels and changes in the UK.

Of course, the built environment is only one influence on people's perceptions of inequality. 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.

The second half of this paper explores patterns of local inequality in the UK. What the data reveals is 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*. Further analysis examining the dispersion of neighbourhood inequality within cities suggests a high degree of economic segregation – most neighbourhoods appear to be equal (either equal and rich or equal and poor). Further research is needed to understand the implications of this economic segregation across neighbourhoods and its impact on important behavioural outcomes.

I also explore how local inequality has changed over the period 1999-2019. I find that inequality has declined on average across England and Wales in cities, towns and neighbourhoods. 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. This highlights the benefits of taking a 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.

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 can be used to shed light on many research questions seeking to understand the consequences of economic inequality. For example, there is ongoing scholarly debate regarding whether inequality affects voter turnout (Cancela & Geys, 2016; Stockemer & Scruggs, 2012), consumer borrowing (Coibion et al., 2014; B. K. 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). Taking pro-social behaviour as an example, it is possible that the theorised relationship between inequality and charitable donation is, to some extent, washed out by the spatial resolution utilised. For example, (Côté et al., 2015) use US state-level inequality, but it is hard to imagine that individuals in Sacramento have similar experiences to those in San Francisco. 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.

2.7 Annex

Figure A.1: Correlation matrix for inequality measures (LSOA-level)

	Gini	Coefficient of variation	Top 1%	Nine:ten	Nine:five	Five:ten
LSOA						
Gini	1.000	0.867	0.658	0.901	0.857	0.574
Coefficient of variation	0.867	1.000	0.851	0.717	0.735	0.394
Top 1%	0.658	0.851	1.000	0.482	0.533	0.213
Nine:ten	0.901	0.717	0.482	1.000	0.805	0.739
Nine:five	0.857	0.735	0.533	0.805	1.000	0.226
Five:ten	0.574	0.394	0.213	0.739	0.226	1.000
Towns & Cities						
Gini	1.000	0.839	0.768	0.940	0.912	0.641
Coefficient of variation	0.839	1.000	0.896	0.727	0.728	0.469
Top 1%	0.768	0.896	1.000	0.612	0.622	0.384
Nine:ten	0.940	0.727	0.612	1.000	0.856	0.793
Nine:five	0.912	0.728	0.622	0.856	1.000	0.375
Five:ten	0.641	0.469	0.384	0.793	0.375	1.000

2.7.1 Relationship between housing value inequality and income inequality

One objection to computing economic inequality based on housing values is that the value of a house oftentimes doesn't correspond with the tenure of its inhabitants. Households who do not own their home outright cannot lay claim to its worth. One argument against this objection is that if a household lives in a property that is relatively high in value, the inhabitants will likely be relatively well off in economic terms whether they are renting or not, and vice versa. Because of this, I expect to see a strong association between housing value inequality and income inequality. I test to see whether this is the case. The main rationale for using housing values, however, is that there is not sufficiently granular or detailed information on incomes in the UK. As a result, in evaluating how housing value inequality correlates with other measures of inequality, I am largely confined to more aggregated levels.

I first examine how the Gini coefficient of housing values correlates with wage inequality calculated from the Annual Survey of Hours and Earnings (ASHE), a 1% sample of employees in the UK based on the PAYE register. The advantage of this dataset is that its size allows us to measure inequality down to the Parliamentary Constituency (PC) level (total number of areas = 650), although this is expected to still be noisy, with an average of 189 observation per PC (which far less than the equivalent number for housing values, which is 35,341). Moreover, ASHE does not perfectly represent the income distribution as it does not capture the self-employed or non-labour sources of income.

Table A.1 provides univariate regression results for housing value inequality on income inequality derived from ASHE at different levels of aggregation, which we take as the PC and LAD – Columns 1 to 2 respectively. The coefficients are standardised to ease interpretation. The relationship is substantive – a 1 standard deviation increase in the Gini of housing value inequality is associated with a 0.546 and 0.58 standard deviation increase in the income Gini at the PC and LAD levels respectively. As we shouldn't expect a measure based on housing values to be perfectly correlated with income inequality, the strong correlation between them, despite the noisiness of the income inequality measure, is reassuring and suggests that measures based on housing values are appropriately describing the relevant economic distribution.

Table A.1: Relationship between wage (ASHE) and housing value inequality

	Dependent variable:	
	Gini income inequality	
	PC	LAD
	(1)	(2)
Gini housing value	0.546***	0.580***
	(0.064)	(0.083)
Mean income observations per area	189.26	319.06
Mean housing observations per area	35340.84	60134.93
Observations	627	361
R^2	0.103	0.119
Note:	*p<0.1; **p<0.05; ***p<0.01	

While neighbourhood-level inequality estimates do not exist outside this paper as far as I'm aware, attempts have been made to use ONS LSOA income estimates to construct inequality measures for larger areas (Rae & Nyanzu, 2019). The ONS provides the estimated percentage of households within each area with an income that falls within a range, with the data only covering England and Wales.[15] The income bands are: 0; (0-5k]; (5k-10k]; (10k-15k]; (15k-20k]; (20k-30k]; (30k-40k]; (40k-60k]; and over 60k. Therefore, one can calculate a Gini coefficient for each LSOA by taking the midpoint of the band and assigning it to households in proportion.

This approach has at least two downsides. First, the highest income category is 60k and above, which is a rather low top end cutoff value, and it is therefore not clear what income to apply for the proportion of households above this value (Rae & Nyanzu (2019) take 70k). Second, research suggests the grouping of continuous values into a small number of bands results in substantial downward bias to the resulting estimated Gini (Van Ourti & Clarke, 2011).

Nevertheless, I use the ONS LSOA income estimates for 2015-16 (the latest release as of this writing) and apply this approach to construct an alternative LSOA-level Gini. I then see how correlated the measures are with the Gini based on housing values. Table A.2 provides these

[15] Data is available publicly here: https://www.ons.gov.uk/census/censustransformationprogramme/administrativedatacensusproject/administrativedatacensusresearchoutputs/populationcharacteristics/researchoutputsincomefrompayasyouearnpayeandbenefitsfortaxyearending2016.

results using univariate regression with standardised coefficients, indicating once more a strong correlation between housing and income inequality measures, despite the coarseness and top coding of the income groups in the latter. Column 1 of Table A.2 provides the correlation with the LSOA income Gini (0.56), and Colums 2 and 3 replicate the analysis for ASHE, i.e. taking inequality at the LAD and PC levels, using the banded income data (0.47 and 0.47 respectively).

Table A.2: Relationship between income (PAYE) and housing values inequality

	Dependent variable:		
	Gini PAYE income inequality		
	LSOA	PC	LAD
	(1)	(2)	(3)
Gini housing value	0.559^{***}	0.466^{***}	0.471^{***}
	(0.004)	(0.038)	(0.050)
Observations	34,740	533	317
R^2	0.313	0.221	0.223
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

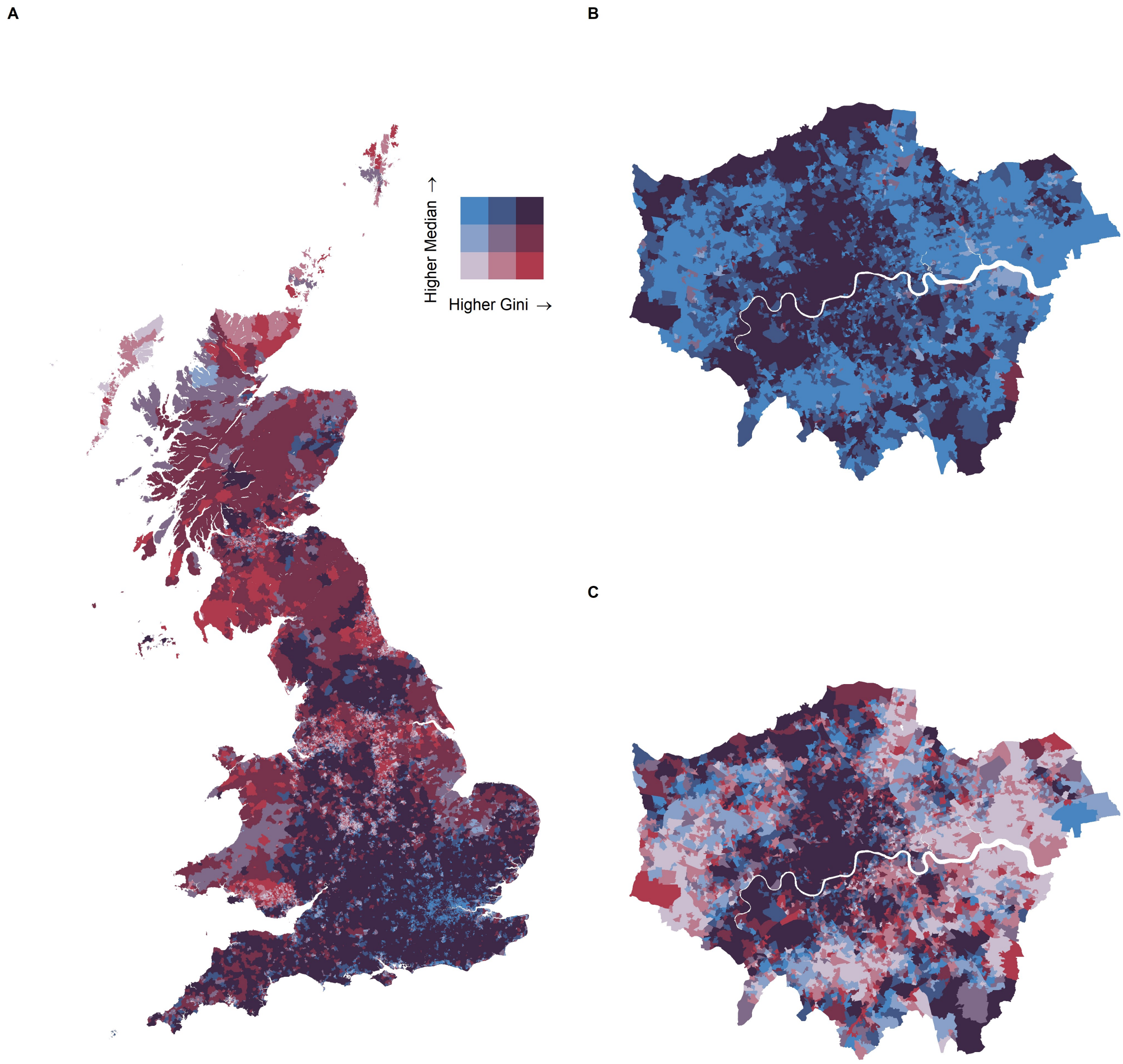
2.7.2 Bivariate spatial analysis

Areas that are relatively unequal or equal can vary in terms of median wealth. One reason to examine this bivariate spatial relationship is to evaluate the extent of neighbourhoods that are equal and poor versus equal and rich. To examine this variation and differentiate between area types, I map the relationship between inequality and median property value (log scale) in Figure A.2. I scale both variables so that they each have a mean of 0 and a standard deviation of 1, and segment inequality and median value using quantiles method and contrasting colour scheme.

Panel A of Figure A.2 shows the bivariate map for the UK. We can thus see a more nuanced representation of within-area inequality, with much of Wales, the Midlands and the North of England relatively unequal but poor as compared with the South of England and Scotland. It is mainly cities such as Birmingham, Manchester, Liverpool and Cardiff which have LSOAs which are both poor and equal, while urban areas in the South West and London, as well as rural areas in the North of Scotland, are relatively equal and rich.

Once again, I pull out London (Panel B of Figure A.2) to see that, given the uniformly high property values in the capital relative to the rest of the country, there is not much difference in this visualisation to that of Figure 3. I therefore re-scale and re-segment London on its own to account for its position relative to other regions of the UK (Panel C). We thus are able to see pockets of inequality within the city's relatively poor areas in the East, South and West.

Figure A.2: Bivariate distribution of LSOA-level inequality and median property value



3 The determinants of local inequality

Abstract: *What leads some neighbourhoods to be more unequal than others? While a growing body of work investigates the determinants of sub-national inequality, studies generally do not go below the level of cities. There is therefore limited understanding of the causes of neighbourhood-level inequality. I investigate this question using granular measures of inequality in the UK based on housing values. I find that the determinants of neighbourhood inequality are mostly similar to those of urban areas in the UK and elsewhere – educational attainment in particular is a key factor. However, I also find that the presence of exogenous amenities, e.g. rivers, and listed buildings, are substantive drivers of inequality at the neighbourhood-level but not for urban areas as a whole, contrary to related work in other countries.*

3.1 Introduction

Recent years have seen a growing interest in the determinants of urban and regional inequality, with papers covering the US (Florida & Mellander, 2016; Glaeser et al., 2009), UK (N. Lee et al., 2016) and Canada (Bolton & Breau, 2012; Marchand et al., 2020). Some recent work has examined the drivers of inequality at a more local level, for example Hortas-Rico & Rios (2019) explore municipalities across Spain, while other works have looked at specific cities in France (Najib, 2020) and South Africa (Hamann & Horn, 2021). There is currently no empirical evidence, however, for why some neighbourhoods are more unequal than others for the UK. What drives rich and poor to live side by side?

This is an important question for a number of reasons. First, uncovering the determinants of local inequality provides insight into the how the lived experience of residents varies with inequality. For example, if inequality is associated with ethnic diversity then people living in less equal places are also more likely to be exposed to people of different backgrounds (see Chapter 6). Another example might be in relation to the kinds of amenities residents have access to. Moreover, by understanding how local inequality translates into daily experiences and observation (Suss, 2021), we might be able to uncover pathways through which inequality affects attitudes and behaviour. Second, understanding what factors explain why some places are more unequal than others can inform policymakers concerned with the potential benefits and pitfalls of economically diverse neighbourhoods (Cheshire, 2007; G. Galster, 2007; Meen & Gibb, 2005; Ostendorf et al., 2001), or in order to aid in avoiding social ills associated with neighbourhood inequality, e.g. crime (Morenoff et al., 2001; Whitworth, 2013).

This paper explores the determinants of neighbourhood-level inequality in the UK. For inequality, I utilise unique data providing a granular picture of economic discrepancies based on housing values (see Chapter 2 of this thesis for details of the data and measure used). I merge this information with data on socio-demographic composition, housing tenure, and local amenities from the UK census, the Ordnance Survey, and other sources. I estimate spatial error models to explore how these characteristics relate to local inequality, producing a richer picture of the determinants of inequality in the UK than has been available to date.

In line with studies at the urban and regional levels, I find that the composition of skills, proxied by the percent of adult residents with a university degree or above, is the most important factor determining neighbourhood inequality, however its relationship with inequality is non-linear and concave. Other less important but still significant demographic and labour market factors are: the share of workers employed in manufacturing occupations; the percent of females in employment; the ethnic composition of residents; and the age profile of the area. These findings are robust to different measures of local inequality and sub-sample analyses, i.e. whether looking solely at neighbourhoods within urban or rural areas. I find evidence that changes in these neighbourhood characteristics over the period 1991 and 2011 predict changes in local inequality over the period 1999-2019, hinting at their potentially causal role.

I also find that the concentration of housing tenure (i.e. whether homes are owned, mortgaged, privately or socially rented) is an important factor that is associated with lower neighbourhood inequality. Moreover, increased concentration of housing tenure within neighbourhoods between 1991 and 2011 is the most important factor explaining changes in inequality over time. This finding, coupled with the fact that inequality has been declining on average across neighbourhoods in the UK (see Chapter 2), suggests that neighbourhoods are becoming more segregated within urban and rural areas alike. This might due to ineffective planning policies moving away from encouraging mixed development neighbourhoods, or it might be a result of gentrification processes which are changing the makeup of once mixed communities (Tunstall & Lupton, 2010).

I examine whether amenities matter for local inequality in the UK. There is evidence from the US to suggest that the presence of natural amenities are responsible for persistently high incomes in urban areas (S. Lee & Lin, 2018), and that modern amenities (e.g. cultural offerings) have fueled increases in urban inequality (Diamond, 2016). I examine whether the presence of 'historic/exogenous' (e.g. rivers, listed buildings, world heritage sites) and 'modern/endogenous' (e.g. playgrounds, sports fields) amenities, identified by Brueckner et al. (1999), are drivers of local inequality in the UK. I find that amenities of both kinds are substantively associated with neighbourhood-level inequality – a one standard deviation increase in the presence of listed buildings, for example, is associated with a 10% increase in neighbourhood inequality, controlling for median house value and other important factors. Amenities are not important, however, when looking at urban areas in aggregate.

Finally, I adopt a multi-scalar approach (Cavanaugh & Breau, 2018), comparing and contrasting the determinants of neighbourhood inequality with those of urban inequality. This analysis highlights certain shared determinants of inequality across these different levels of aggregation, including skills composition and ethnic diversity, but also determinants that only matter at the local or urban level, such as amenities and unemployment respectively.

The rest of this paper is proceeds as follows. Section 3.2 details the data and methodology utilised, 3.3 provides the results, and 3.4 concludes with a discussion and overview of the policy implications.

3.2 Data and methodology

I gather data from the 1991 and 2011 UK census on known determinants of urban and regional level inequality at the neighbourhood-level (Glaeser et al., 2009; N. Lee et al., 2016; Marchand et al., 2020). In particular, I obtain data on demographic and labour market characteristics, skills, occupations, and housing tenure. For demographic and labour market characteristics, I include the natural log of neighbourhood population, the percent of adults unemployed, the percent of females that are employed, and the percent of workers that work part-time. I also include the percent of residents who are old (65 years and older) and young (under 18 years of age). I also include a measure of ethnic composition, taken as the percent of residents who self-identify as non-white. For skills, I take the percent of adult residents who have a university degree or above (i.e. qualification level 4 and above). For occupation, I take the percent of workers who are employed in manufacturing. Finally, I also include the natural log of the median house value for the area.

I augment this data with information on the housing tenure composition of the neighbourhood. In particular, I include a measure of the concentration of housing tenure, broken down into four categories (owned outright, owned with a mortgage, private rented, and social rented), using the Herfindahl-Hirschman Index (HHI), and the percent of housing that is socially rented (i.e. from the Local Authority or housing association).

Lastly, I include a number of variables for amenities, covering both historical and modern types, as defined by Brueckner et al. (1999). For historical/exogenous amenities, I take rivers, listed buildings, world heritage sites, and registered parks and gardens. For modern amenities, I take green sites (which comprise playgrounds, sports sites, and other green spaces) and rail stations. Listed buildings, world heritage sites, and registered parks and gardens data are obtained from Heritage England, Scotland, Wales and Northern Ireland. Information on green sites and rivers are retrieved from the Ordnance Survey.[16] Locations of train stations in Great Britain are obtained from Pope (2017). Table 8 provides summary statistics.

The inequality data is the same as that which was presented in Chapter 2, with the preferred measure taken as the Gini coefficient. In terms of spatial scale, the neighbourhood is defined once more as the LSOA (N = 41,729 for the entire UK), and the urban level is taken as all towns and cities in the UK (N = 596).

Given the likelihood that our variables are not randomly spatially distributed, I perform a Moran's I test to check for the presence of spatial autocorrelation. The null hypothesis is indeed rejected ($p < 0.01$), which indicates that a spatial regression model is warranted. As is typical, I fit both a spatial lag and spatial error model and perform a Lagrange Multiplier test to select between them, which indicates the superiority of the spatial error model. I therefore specify a spatial error model in the following form:

$$Gini_i = \alpha + \beta X_i + \gamma Z_i + \epsilon_i$$

Where, $\epsilon_i = \lambda \sum_{j=1}^{N} W_{ij}\, \epsilon_i + \mu_i$

[16] The data on green sites and rivers is available publicly here: https://osdatahub.os.uk/downloads/open#OPGRSP

$Gini_i$ is the estimated level of inequality in LSOA i, X is the vector of determinants, Z are fixed effects for UK regions, λ is the spatial autocorrelation coefficient, W is the spatial weight matrix, which I calculate using the Queen's criterion with all adjoining neighbours receiving equal weight, and μ_i is the spatially autocorrelated error term.

Table 8: Descriptive statistics for inequality determinants

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Gini	41,742	0.195	0.066	0.018	0.145	0.238	0.649
Top 1%	41,742	0.031	0.013	0.012	0.023	0.036	0.393
Nine:ten	41,742	2.484	0.897	1.000	1.884	2.873	30.286
Ln(Population)	42,619	7.250	0.341	4.990	7.178	7.438	9.024
Median house price	41,742	12.266	0.603	10.571	11.828	12.679	15.339
Unemployed (%)	42,619	4.473	2.511	0.181	2.597	5.814	20.464
Female employed (%)	42,619	57.431	9.204	3.028	52.844	63.323	86.456
Part-time employed (%)	42,619	0.138	0.027	0.008	0.125	0.156	0.278
Aged 65+ (%)	42,619	16.736	7.205	0.000	11.549	21.272	73.762
Aged under 18 (%)	42,619	20.060	4.536	0.541	17.495	22.581	47.062
Uni Degree or above (%)	42,619	29.465	13.972	3.456	18.757	37.931	93.613
Non-white (%)	42,619	11.567	17.200	0.000	1.855	12.533	99.281
Manufacturing employed (%)	42,619	8.973	4.494	0.000	5.702	11.582	45.102
Social rent (%)	42,619	18.244	17.805	0.000	4.200	27.700	98.400
Housing tenure HHI	42,619	0.560	0.158	0.250	0.430	0.681	1.000
Rivers	42,194	3.533	9.362	0.000	0.000	2.000	89.000
Green sites	42,619	4.290	3.927	0	1	6	39
Listed buildings	42,192	9.466	21.201	0.000	0.000	7.000	144.000
Rail stations	42,619	0.068	0.287	0	0	0	10
Parks and gardens	42,619	0.121	0.434	0	0	0	11
World heritage sites	42,619	0.028	0.240	0	0	0	6

3.3 Results

3.3.1 Determinants of inequality at the neighbourhood level

Table 9 provides the baseline results for the spatial error model with region fixed effects. Column 1 provides the simplest model, i.e. without squared terms or amenity variables. Column 2 adds the squared terms, and Column 3 introduces the amenity variables. I standardise all variables so that the coefficient sizes are comparable. Across all models, I find that the single most important factor is the percent of residents with a university degree or above, with a coefficient of 0.515 in Column 1. The relationship between skills and inequality is non-linear, however, with the coefficient on the squared term negative in Columns 2 and 3, reflecting a concave relationship. This makes intuitive sense – areas which have very few university graduates or are mostly comprised of university graduates are expected to be relatively equal, whereas those that contain a mix of low skilled and high skilled residents are expected to be more unequal.

The second most important determinant is the concentration of housing tenure, with a coefficient of -0.37 in the full model with amenities. In other words, the more concentrated the area is in terms of housing tenure, the more equal. I also find a negative and substantively large coefficient for the ethnicity variable (β = -0.135 in Column 3). Next in terms of size are two amenity variables – green sites (β = 0.116) and listed buildings (β = 0.103). The coefficients on rivers, parks and gardens, and rail stations are also significant but relatively small in size.

The older the population and the higher the share of those employed in manufacturing, the higher the level of inequality in the neighbourhood. As with skills, the squared term for the manufacturing variables is significant and negative, suggesting a concave relationship with inequality. Interestingly, the coefficient for the main effect of median house prices turns negative when introducing the amenity variables in Column 3. The share of houses in the neighbourhood that are social rented exhibits a similar non-linear and convex relationship with inequality.

Column 4 provides the OLS model (i.e. without accounting for spatial effects) using the same variables as in Column 3. The estimated relationships are largely the same in direction and size.

Table 9: Determinants of neighbourhood-level inequality

	Gini (2019)			
	Simple	Non-linearities	Amenities	OLS
	(1)	(2)	(3)	(4)
Ln(Population)	0.116***	0.094***	0.033***	0.042***
	(0.007)	(0.006)	(0.007)	(0.007)
Ln(Median house price)	0.087***	0.042***	-0.083***	-0.085***
	(0.013)	(0.013)	(0.013)	(0.011)
Ln(Median house price)^2		0.074***	0.077***	0.153***
		(0.004)	(0.004)	(0.003)
Unemployed (%)	0.011	0.011	0.006	0.006
	(0.008)	(0.008)	(0.008)	(0.008)
Female employed (%)	-0.027***	-0.082***	-0.075***	-0.041***
	(0.007)	(0.007)	(0.007)	(0.006)
Part-time employed (%)	-0.073***	-0.057***	-0.051***	-0.111***
	(0.006)	(0.006)	(0.006)	(0.006)
Aged 65+ (%)	0.120***	0.110***	0.085***	0.138***
	(0.006)	(0.006)	(0.006)	(0.005)
Aged under 18 (%)	-0.065***	-0.043***	-0.036***	0.022***
	(0.006)	(0.006)	(0.006)	(0.005)
Uni Degree or above (%)	0.515***	0.769***	0.731***	0.652***
	(0.010)	(0.011)	(0.011)	(0.009)
Uni Degree or above (%)^2		-0.206***	-0.177***	-0.152***
		(0.004)	(0.004)	(0.004)
Non-white (%)	-0.075***	-0.174***	-0.135***	-0.133***
	(0.009)	(0.009)	(0.009)	(0.006)
Manufacturing employed (%)	-0.007	0.076***	0.083***	0.113***
	(0.007)	(0.009)	(0.008)	(0.007)
Manufacturing employed (%)^2		-0.023***	-0.021***	-0.023***
		(0.003)	(0.003)	(0.003)
Social rent (%)	-0.037***	-0.159***	-0.082***	-0.081***
	(0.007)	(0.012)	(0.012)	(0.011)
Social rent (%)^2		0.089***	0.046***	0.031***
		(0.005)	(0.005)	(0.005)
Housing tenure HHI	-0.363***	-0.494***	-0.370***	-0.301***
	(0.006)	(0.009)	(0.009)	(0.009)
Rivers			0.047***	0.066***
			(0.005)	(0.005)
Green sites			0.116***	0.137***
			(0.004)	(0.005)
Listed buildings			0.103***	0.112***
			(0.005)	(0.005)
Parks and gardens			0.023***	0.025***
			(0.004)	(0.004)
World heritage sites			0.038	0.010
			(0.036)	(0.029)

Rail stations			0.015***	0.022***
			(0.003)	(0.004)
Constant	0.109***	0.117***	0.072*	-0.0004
	(0.042)	(0.040)	(0.037)	(0.021)
Fixed effect	Region	Region	Region	Region
Observations	41,742	41,742	40,948	40,948
R^2				0.471
Log Likelihood	-44,744.950	-43,377.060	-41,496.300	
sigma^2	0.464	0.436	0.418	
Akaike Inf. Crit.	89,541.910	86,814.120	83,064.600	
Wald Test (df = 1)	12,621.610***	10,934.950***	9,787.671***	
LR Test (df = 1)	9,444.805***	8,156.175***	6,582.829***	
Note:				*p<0.1; **p<0.05; ***p<0.01

I next conduct a number of checks to see whether the factors explaining neighbourhood-level inequality are robust. First, because Table 9 included all LSOAs, Table A.3 in the Annex splits the data into sub-samples, looking separately at neighbourhoods within urban areas only (Column 1), towns and cities separately (Columns 2 and 3 respectively), and rural neighbourhoods (Column 4). The findings are consistent in all these models, albeit some of the coefficient sizes differ in intuitive ways. For example, the association between rivers and LSOA inequality is far smaller when looking at the rural only subset. Conversely, listed buildings are more strongly associated with neighbourhood inequality within cities, highlighting the importance of these amenities for drawing in wealthier inhabitants, thus increasing local inequality.

Table A.4 in the Annex provides the results for alternative inequality measures, using the Top 1% concentration and three percentile ratios, 90:10, 90:50 and 50:10. The findings vary somewhat depending on the measure of inequality used. The education variable continues the be the most important determinant except for when the outcome variable is the 90:50 ratio, where it is relatively much smaller. This is not that surprising – the percent of residents who are highly educated does not affect inequality in the top half of the distribution as much as it does for the bottom half or the top to bottom ratio. The coefficients on the amenity values are largely consistent regardless of inequality measure used.

Finally, Table A.5 presents the results for a specification where instead of data from the 2011 census, I use data from the 1991 census. The results demonstrate that the relationships observed in Table 9 are persistent over time – the 1991 variables are strongly predictive of neighbourhood inequality in 2019. The percent of residents with a university degree in 1991 is the second most important factor for contemporary inequality levels, behind housing tenure concentration.

3.3.2 Determinants of changes in neighbourhood inequality

Table 10 presents regression results for both the neighbourhood and city-level where all variable are differenced between 2011 and 1991 (2019 and 1999 for the Gini). Amenities are omitted from Table 10 because they either do not change over time (e.g. rivers), or I am not able to obtain data for 1991 (e.g. green sites). The results reveal that both neighbourhoods and urban areas that saw an increase in skilled residents, as proxied by the percentage point change in adults with a university degree, experienced substantial increases in inequality (β = 0.066 and 0.42 respectively for neighbourhoods and urban areas). The squared term is also positive and significant at the neighbourhood level, suggesting the effect is even stronger for areas which saw relatively large percentage point increases.

On the other hand, areas that saw increases in the concentration of housing tenures at the neighbourhood level saw substantial decreases in inequality (β = -0.271). This provides suggestive evidence that the patterns of declining neighbourhood-level inequality is a result of increasing segregation (see Figure 5).

Table 10: Change in inequality and determinants (1999 to 2019) at neighbourhood level

	Gini change (1999-2019)	
	Neighbourhood	Neighbourhood
	(1)	(2)
Change Ln(Population)	0.0004	0.0002
	(0.006)	(0.006)
Change Ln(Median house price)	-0.128***	-0.145***
	(0.007)	(0.008)
Change Ln(Median house price)^2		0.009***
		(0.002)
Change Unemployed (%)	-0.057***	-0.054***
	(0.008)	(0.008)
Change Female employed (%)	-0.006	-0.0001
	(0.009)	(0.010)
Change Part-time employed (%)	-0.028***	-0.029***
	(0.008)	(0.008)
Change Aged 65+ (%)	-0.039***	-0.035***
	(0.009)	(0.009)
Change Aged under 18 (%)	0.001	0.002
	(0.008)	(0.008)
Change Uni Degree or above (%)	0.080***	0.066***
	(0.009)	(0.010)
Change Uni Degree or above (%)^2		0.014***
		(0.005)
Change Non-white (%)	-0.018*	-0.014
	(0.010)	(0.010)
Change Manufacturing employed (%)	0.0004	0.001
	(0.007)	(0.007)
Change Manufacturing employed (%)^2		0.001
		(0.004)
Change Social rent (%)	-0.024**	-0.032***
	(0.010)	(0.011)
Change Social rent (%)^2		0.004
		(0.008)
Change Housing tenure HHI	-0.271***	-0.271***
	(0.018)	(0.018)
Constant	-0.134***	-0.161***
	(0.012)	(0.015)
Fixed effect	None	None
Observations	27,885	27,885
Log Likelihood	-38,620.890	-38,606.810
$sigma^2$	0.922	0.921

Akaike Inf. Crit.	77,271.770	77,251.610
Wald Test (df = 1)	1,087.866***	1,054.965***
LR Test (df = 1)	1,017.227***	1,013.083***
Note:		*p<0.1; **p<0.05; ***p<0.01

3.3.3 Determinants of inequality at the urban level

Finally, I examine whether the same relationships exist at the urban level of aggregation – i.e. for all towns and cities in the UK. Table 11 presents these results using simple OLS as a Moran's I test reveals a lack of spatial autocorrelation at this level (p = 0.75). Column 1 to 3 replicates the specifications in the main regression analysis of Table 9.

As with the neighbourhood-level analysis, the proxy for skills composition is the single most important factor driving urban inequality in the UK (β = 0.86 in Column 3). Unlike the neighbourhood-level regressions, the coefficients for the housing tenure variables are not significant. Amenities are also no longer important. This is somewhat surprising, as the literature on the importance of amenities for affecting residential composition is generally situated at the urban level (Brueckner et al., 1999; Glaeser et al., 2008).

There is again a convex relationship between median income and inequality, suggesting that poorer and richer cities tend to be more unequal than cities at the middle of the distribution in terms of median housing value. The unemployment rate, which was not significant at the neighbourhood-level, turns out to be an important factor at the urban level (β = 0.227 in Column 3).

Table 11: Determinants of urban inequality

	Gini (2019)		
	Simple	Non-linearities	Amenities
	(1)	(2)	(3)
Ln(Population)	0.268***	0.259***	0.254***
	(0.043)	(0.044)	(0.045)
Ln(Median house price)	-0.462***	-0.492***	-0.459***
	(0.083)	(0.079)	(0.082)
Ln(Median house price)^2		0.210***	0.203***
		(0.023)	(0.023)
Unemployed (%)	0.225***	0.203***	0.227***
	(0.051)	(0.048)	(0.051)
Female employed (%)	-0.061	-0.017	-0.021
	(0.045)	(0.046)	(0.047)
Part-time employed (%)	-0.175***	-0.130***	-0.134***
	(0.039)	(0.037)	(0.038)
Aged 65+ (%)	0.181***	0.169***	0.169***
	(0.040)	(0.038)	(0.039)
Aged under 18 (%)	0.109***	0.050	0.066
	(0.038)	(0.040)	(0.041)
Uni Degree or above (%)	0.881***	0.861***	0.860***
	(0.053)	(0.055)	(0.057)
Uni Degree or above (%)^2		-0.078***	-0.086***
		(0.024)	(0.025)
Non-white (%)	-0.075*	-0.062	-0.068*
	(0.040)	(0.039)	(0.041)
Manufacturing employed (%)	0.076**	0.009	0.001
	(0.034)	(0.037)	(0.038)
Manufacturing employed (%)^2		0.033**	0.038**
		(0.016)	(0.017)
Social rent (%)	0.204	0.082	0.289
	(0.381)	(0.398)	(0.443)
Social rent (%)^2		-0.006	-0.015
		(0.009)	(0.024)
Housing tenure HHI	-0.092	0.076	-0.349
	(0.392)	(0.372)	(0.590)
Rivers			0.180
			(0.118)
Green sites			-0.224
			(0.376)
Listed buildings			0.023
			(0.112)
Parks and gardens			0.195

			(0.209)
World heritage sites			0.053
			(0.108)
Rail stations			0.173
			(0.385)
Constant	0.128	-0.267*	-0.182
	(0.139)	(0.140)	(0.148)
Fixed effect level	Region	Region	Region
Observations	609	609	586
R^2	0.672	0.716	0.715
Note:			*p<0.1; **p<0.05; ***p<0.01

3.4 Discussion and conclusion

In this paper, I provide the first examination of the determinants of neighbourhood inequality in the UK. Hitherto studies have focused only as far down as the urban level (N. Lee et al., 2016), whereas the data presented here allows me to adopt a multi-scalar approach, which I do down to the level of neighbourhoods. The results indicate that the determinants of inequality vary across the neighbourhood and urban levels, highlighting the importance of fine-grained analysis of the patterns and determinants of inequality.

I find that, regardless of which geographical scale is chosen, the composition of skills is a key determinant affecting levels of inequality, albeit in a concave fashion. Where the determinants differ from the urban to the neighbourhood scale in relation to housing tenure and amenities. Neighbourhoods with high concentrations of tenure, e.g. home owners, are less economically diverse and more equal. Regarding amenities, both exogenous and endogenous varieties are substantive factors affecting neighbourhood inequality, although not at the level of cities.

The findings here can be used to understand how the lived experiences of people varies by level of inequality. Individuals living in a neighbourhood with high levels of inequality are more likely to live among a people with mixed levels of education and ethnic backgrounds. They are also likely to live in places which have a mix of different housing tenures and include green sites and listed buildings. These factors may act as inputs into people’s perceptions of local inequality and impact upon their attitudes and behaviours as a result.

These findings also provide policymakers and urban planners with potential tools to with which to change the economic diversity of neighbourhoods. This could involve, for example, decisions around the placement of green sites and the development of education and skills programmes. Future work should explore the longitudinal impact of such policies on local inequality, adopting quasi-experimental designs where possible, to provide further insight.

The work is not without limitations, of course, and these suggest avenues for further research. First, this paper cannot account for population flows between neighbourhoods and urban areas. One response to extreme levels of neighbourhood inequality might be to simply move to a different location. While I don't have access to detailed information on population flows between neighbourhoods, future work might rectify this by tapping alternative data sources which might provide this information. For example, the studies are increasingly using anonymised location data from mobile phones and other sources to identify people's home and work locations (Athey et al., 2020; Couture et al., 2020; Dash et al., 2014; Davis et al., 2019). This type of data could potentially be used longitudinally to understand patterns of residential flows.

Second, while the work presented here includes many determinants, from variables capturing socio-demographic compositions to amenities of a range of types, not all possible determinants of interest were included in this work. Future work could build upon the current investigation adding complementary data sources which capture features of the local environment including, for example, its 'scenicness' (Seresinhe et al., 2015) and coastal proximity (Garrett & Fleming, 2019). Despite these limitations, the current work provides valuable insights to the social and physical environments of those living in areas of differing levels of inequality in the UK.

3.5 Annex

Table A.3: Robustness check – sub-group analysis

	Gini (2019)			
	Cities and Towns	Cities	Towns	Rural
	(1)	(2)	(3)	(4)
Ln(Population)	0.055***	0.056***	0.046***	-0.031**
	(0.008)	(0.010)	(0.012)	(0.012)
Ln(Median house price)	-0.080***	-0.050***	-0.153***	-0.083***
	(0.015)	(0.018)	(0.026)	(0.025)
Ln(Median house price)^2	0.071***	0.050***	0.108***	0.132***
	(0.004)	(0.005)	(0.009)	(0.010)
Unemployed (%)	0.013	0.005	0.060***	0.045**
	(0.008)	(0.010)	(0.014)	(0.020)
Female employed (%)	-0.081***	-0.099***	-0.049***	-0.086***
	(0.008)	(0.009)	(0.014)	(0.018)
Part-time employed (%)	-0.041***	-0.027***	-0.091***	-0.087***
	(0.007)	(0.009)	(0.012)	(0.012)
Aged 65+ (%)	-0.026***	-0.022***	-0.060***	-0.119***
	(0.006)	(0.007)	(0.011)	(0.014)
Aged under 18 (%)	0.101***	0.121***	0.047***	-0.047***
	(0.006)	(0.008)	(0.011)	(0.014)
Uni Degree or above (%)	0.746***	0.744***	0.775***	0.624***
	(0.012)	(0.015)	(0.020)	(0.023)
Uni Degree or above (%)^2	-0.166***	-0.152***	-0.201***	-0.233***
	(0.004)	(0.005)	(0.009)	(0.012)
Non-white (%)	-0.129***	-0.119***	-0.412***	0.018
	(0.009)	(0.011)	(0.039)	(0.062)
Manufacturing employed (%)	0.096***	0.104***	0.039***	0.061***
	(0.010)	(0.013)	(0.014)	(0.015)
Manufacturing employed (%)^2	-0.023***	-0.023***	-0.012***	-0.022***
	(0.004)	(0.005)	(0.005)	(0.006)
Social rent (%)	-0.113***	-0.134***	-0.065***	0.034
	(0.013)	(0.016)	(0.023)	(0.026)
Social rent (%)^2	0.064***	0.084***	-0.010	-0.152***
	(0.005)	(0.006)	(0.010)	(0.014)
Housing tenure HHI	-0.393***	-0.426***	-0.329***	-0.223***
	(0.011)	(0.013)	(0.018)	(0.019)
Rivers	0.139***	0.128***	0.152***	0.037***
	(0.010)	(0.015)	(0.013)	(0.005)
Green sites	0.105***	0.103***	0.106***	0.091***

	(0.005)	(0.006)	(0.009)	(0.008)
Listed buildings	0.130***	0.192***	0.069***	0.083***
	(0.007)	(0.011)	(0.010)	(0.007)
Parks and gardens	0.046***	0.048***	0.037***	0.005
	(0.006)	(0.008)	(0.010)	(0.006)
World heritage sites	0.075*	0.083	0.067	-0.079
	(0.044)	(0.060)	(0.058)	(0.050)
Rail stations	0.015***	0.008	0.030***	0.008
	(0.004)	(0.005)	(0.007)	(0.005)
Constant	0.042	0.027	0.010	0.667***
	(0.040)	(0.054)	(0.057)	(0.067)
Fixed effect	Region	Region	Region	Region
Observations	33,428	23,513	9,915	7,520
Log Likelihood	-34,315.500	-24,486.030	-9,486.545	-6,595.076
$sigma^2$	0.428	0.437	0.385	0.329
Akaike Inf. Crit.	68,703.000	49,044.070	19,045.090	13,262.150
Wald Test (df = 1)	7,336.933***	3,689.491***	793.022***	588.867***
LR Test (df = 1)	5,240.560***	4,337.195***	688.682***	524.263***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.4: Robustness check – alternative inequality measures

	Gini (2019)				
	City FE	Top 1%	90:10	90:50	50:10
	(1)	(2)	(3)	(4)	(5)
Ln(Population)	-0.077***	0.015**	0.023***	0.006	0.014*
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Ln(Median house price)	-0.256***	0.247***	-0.723***	1.121***	-0.228***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)
Ln(Median house price)^2	0.109***	0.100***	0.082***	0.065***	0.106***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Unemployed (%)	-0.006	0.010	-0.085***	0.121***	-0.011
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Female employed (%)	-0.067***	-0.063***	-0.078***	-0.022***	-0.053***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Part-time employed (%)	-0.057***	-0.052***	-0.064***	-0.017**	-0.069***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Aged 65+ (%)	-0.049***	0.009	0.013**	-0.012*	-0.027***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
Aged under 18 (%)	0.040***	0.106***	0.040***	0.133***	0.079***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)

Uni Degree or above (%)	0.387***	0.513***	0.824***	0.031***	0.573***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Uni Degree or above (%)^2	-0.094***	-0.118***	-0.159***	-0.050***	-0.135***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Non-white (%)	-0.058***	-0.123***	-0.169***	-0.020**	-0.100***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Manufacturing employed (%)	0.022**	0.105***	0.011	0.178***	0.053***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Manufacturing employed (%)^2	-0.001	-0.023***	-0.010***	-0.034***	-0.009**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Social rent (%)	-0.008	-0.165***	0.127***	-0.384***	-0.016
	(0.014)	(0.012)	(0.014)	(0.014)	(0.013)
Social rent (%)^2	0.049***	0.068***	-0.030***	0.134***	0.026***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Housing tenure HHI	-0.134***	-0.424***	-0.104***	-0.575***	-0.236***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
Rivers	0.078***	0.027***	0.032***	0.019***	0.061***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Green sites	0.101***	0.084***	0.095***	0.046***	0.109***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Listed buildings	0.170***	0.062***	0.100***	-0.026***	0.135***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Parks and gardens	0.040***	0.026***	0.038***	-0.007	0.030***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
World heritage sites	-0.006	0.039	0.072*	-0.002	0.012
	(0.040)	(0.038)	(0.042)	(0.040)	(0.039)
Rail stations	0.008*	0.015***	0.004	0.024***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-0.291***	0.199***	-0.331***	0.694***	-0.112***
	(0.033)	(0.034)	(0.039)	(0.035)	(0.033)
Fixed effect	City	Region	Region	Region	Region
Observations	40,948	40,948	40,948	40,948	40,948
Log Likelihood	-50,562.650	-44,576.960	-48,779.570	-48,191.200	-47,677.820
$sigma^2$	0.680	0.495	0.606	0.597	0.584
Akaike Inf. Crit.	101,197.300	89,225.910	97,631.140	96,454.400	95,427.630
Wald Test (df = 1)	1,929.638***	5,202.095***	10,848.010***	3,174.323***	3,103.537***
LR Test (df = 1)	1,738.642***	4,458.277***	4,284.793***	2,558.225***	2,840.244***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A.5: Robustness check – 1991 data

	Gini (2019)
	1991 data
Ln(Population)	0.018***
	(0.004)
Ln(Median house price)	0.239***
	(0.010)
Ln(Median house price)^2	-0.009**
	(0.004)
Unemployed (%)	-0.144***
	(0.011)
Female employed (%)	-0.190***
	(0.010)
Part-time employed (%)	-0.148***
	(0.008)
Aged 65+ (%)	-0.107***
	(0.009)
Aged under 18 (%)	-0.117***
	(0.011)
Uni Degree or above (%)	0.271***
	(0.008)
Uni Degree or above (%)^2	-0.047***
	(0.003)
Non-white (%)	-0.107***
	(0.009)
Manufacturing employed (%)	-0.051***
	(0.006)
Manufacturing employed (%)^2	0.001
	(0.003)
Social rent (%)	-0.357***
	(0.015)
Social rent (%)^2	0.136***
	(0.008)
Housing tenure HHI	-0.794***
	(0.020)
Constant	0.669***
	(0.040)
Fixed effect	Region
Observations	29,317
Log Likelihood	-31,056.830
sigma^2	0.461
Akaike Inf. Crit.	62,167.650
Wald Test	5,451.698*** (df = 1)
LR Test	4,328.355*** (df = 1)
Note:	*p<0.1; **p<0.05; ***p<0.01

4 Local economic inequality leads higher income individuals to be more generous

Abstract: *There is ongoing debate about whether the relationship between income and pro-social behaviour depends on economic inequality. Studies investigating this question differ in their conclusions but are consistent in measuring inequality at aggregated geographic levels (i.e. at the state, region, or country-level). I hypothesise that local, more immediate manifestations of inequality are important for driving pro-social behaviour, and test the interaction between income and inequality using a much finer geographical resolution. I first analyse the charitable giving of US individuals and households, using ZIP-code level measures of inequality and data on tax deductible charitable donations reported to the IRS (N = 133,870). I then generalise the results to individuals in the UK using a large-scale household survey (N = 39,289) and neighbourhood-level inequality measures. In both samples I find robust evidence of a significant interaction effect, albeit in the opposite direction as that which has been postulated – higher local inequality leads higher income individuals to behave more pro-socially rather than less. Finally, I investigate whether greater contact between rich and poor in local unequal areas is driving the findings – respondents are significantly more likely to say they have at least some friends who have different incomes to themselves if they live in an unequal neighbourhood, but this does not mediate the relationship between inequality and pro-social behaviour.*

4.1 Introduction

How does economic inequality affect pro-social behaviour? This question has become increasingly important as inequality has risen sharply over the last half-century in the US, UK and many other countries (Alvaredo et al., 2018; Piketty & Saez, 2014). Existing research situates the potential effect of inequality on pro-social behaviour within a larger, and largely inconclusive, debate on whether the rich are more or less generous than the poor (Andreoni et al., 2017; Holland et al., 2012; Korndörfer et al., 2015; Piff et al., 2010, 2012). A notable paper finds that the relationship between income and pro-social behaviour depends on inequality, with a negative interaction between inequality at the US state-level and individual income (Côté et al., 2015). However, more recent studies, using data on inequality at the state, region and country-level find no significant interaction effect (Schmukle et al., 2019) and the opposite sign

(Hermanni & Tutić, 2019) when looking at charitable giving and volunteering behaviour. Follow-up analysis using new survey data (Côté & Willer, 2020) has failed to provide clarity (Schmukle & Egloff, 2020).

Understanding whether and how inequality affects pro-social behaviour is critical from a societal perspective. If higher inequality interacts negatively with income to reduce pro-social behaviour, for example reducing the amount of charitable giving, rising inequality might reinforce itself in the absence of countervailing forces (Duquette & Hargaden, 2019). In aggregate, charitable donations by individuals were estimated at over $300bn in the United States in 2019 according to Giving USA, with a large proportion of the total going to education, poverty alleviation, and other organisations which aid in reducing inequality.[17] To put that figure into perspective, the amount the US government spends on poverty alleviation has been estimated at just under $400bn for 2018 (Shaefer et al., 2019).

Scholars investigating the link between inequality and pro-social behaviour generally assume that macro-level inequality is the appropriate spatial unit of analysis, however there is good reason to believe it is not. Importantly, it is not clear whether individuals receive the macro-level inequality 'treatment' for two reasons. First, there is wide variation of local inequality within macro-level areas – for example, individuals in San Francisco and Sacramento, or London and Liverpool don't experience the same level of inequality and generally live in very different contexts. Inequality, as measured by the Gini coefficient on incomes, is 11% larger in San Francisco than Sacramento, and 17% larger in London relative to Liverpool based on the Gini coefficient of housing values.[18] Using a single figure to represent multiple local contexts obscures variability in lived experiences (Suss, 2021). Figure 7 depicts this wide variation for the US by plotting income inequality at the state-level and by ZIP-code – sub-state areas that are better approximations of local communities than states (Velez & Wong, 2017; Wong et al., 2020).

Second, a nascent body of work calls into question whether actual levels of national inequality are accurately perceived. Indeed, perceptions tend to be far off from reality (Chambers et al.,

[17] Information on charitable giving retrieved from Giving USA.
[18] Authors calculation from Gini coefficient at the county-level Bureau (2021) for the US, and housing value inequality derived from Zoopla for the UK – see Suss (2021) for details of this data.

2014; Gimpelson & Treisman, 2018; Kiatpongsan & Norton, 2014; Norton & Ariely, 2011). This is important because perceptions of inequality rather than actual levels have been found to be more relevant for attitudes and behavior (Cruces et al., 2013; Hauser & Norton, 2017; A. Kuhn, 2011). On the other hand, local measures of economic inequality have been shown to be associated with subjective perceptions of national inequality (Cruces et al., 2013; Minkoff & Lyons, 2019; Xu & Garand, 2010). This is because local contexts serve as important sources of information used by individuals to make sense of wider society (G. C. Galster, 2012). This is not only the case for distributional perceptions – in other domains as well, individuals utilise local information when forming judgments about macro variables, e.g. national economic performance or unemployment (Ansolabehere et al., 2014; Reeves & Gimpel, 2012; Weatherford, 1983). Thus, in so far as national assessments of inequality matter for pro-social behaviour, local inequality is likely to be an important influence through its influence on perceptions of national inequality.

Local economic inequality is also likely to affect pro-social behaviour in and of itself. From a theoretical perspective, greater inequality is thought to increase the social distance between economic classes (Côté et al., 2015; Duquette & Hargaden, 2019), thereby attenuating support for poverty alleviation through charitable giving or redistributive policies on the part of the rich. In so far as rising aggregate inequality goes hand in hand with increasing residential segregation (Reardon & Bischoff, 2011), this should indeed result in greater social distance through the logic of greater physical distance. Less contact which arises through residential segregation along economic lines might allow negative stereotypes and stigmatisation to grow (Durante & Fiske, 2017; Lamont et al., 2014).

However, the social distance mechanism would suggest that greater inequality within local areas, where rich and poor have greater opportunity for interactions, could work instead to reduce social distance through greater inter-group contact (Allport et al., 1954; Pettigrew et al., 2011; Pettigrew & Tropp, 2006). This contact could take the form of simple observations of those in relative need or through more economically heterogeneous friendship networks, helping to reduce stigmatisation and increasing empathy (Bailey et al., 2013). Recent experimental evidence provides suggestive evidence of a positive effect, with markers of inequality in local areas increasing support for redistributive policies (Sands, 2017; Sands & Kadt, 2020).

Experienced from a local perspective, economic inequality might therefore have a positive impact on pro-social behaviour. To date, however, there is almost no empirical research that investigates whether local inequality affects individual pro-social behaviour, either directly or when interacted with income. One exception is a study by A. A. Payne & Smith (2015), in which the authors investigate whether changes in income inequality at the level of Canadian urban areas and local communities affects changes in charitable giving. I build on this work here, exploring the effect local inequality has on pro-social behaviour across two studies in the US and UK.

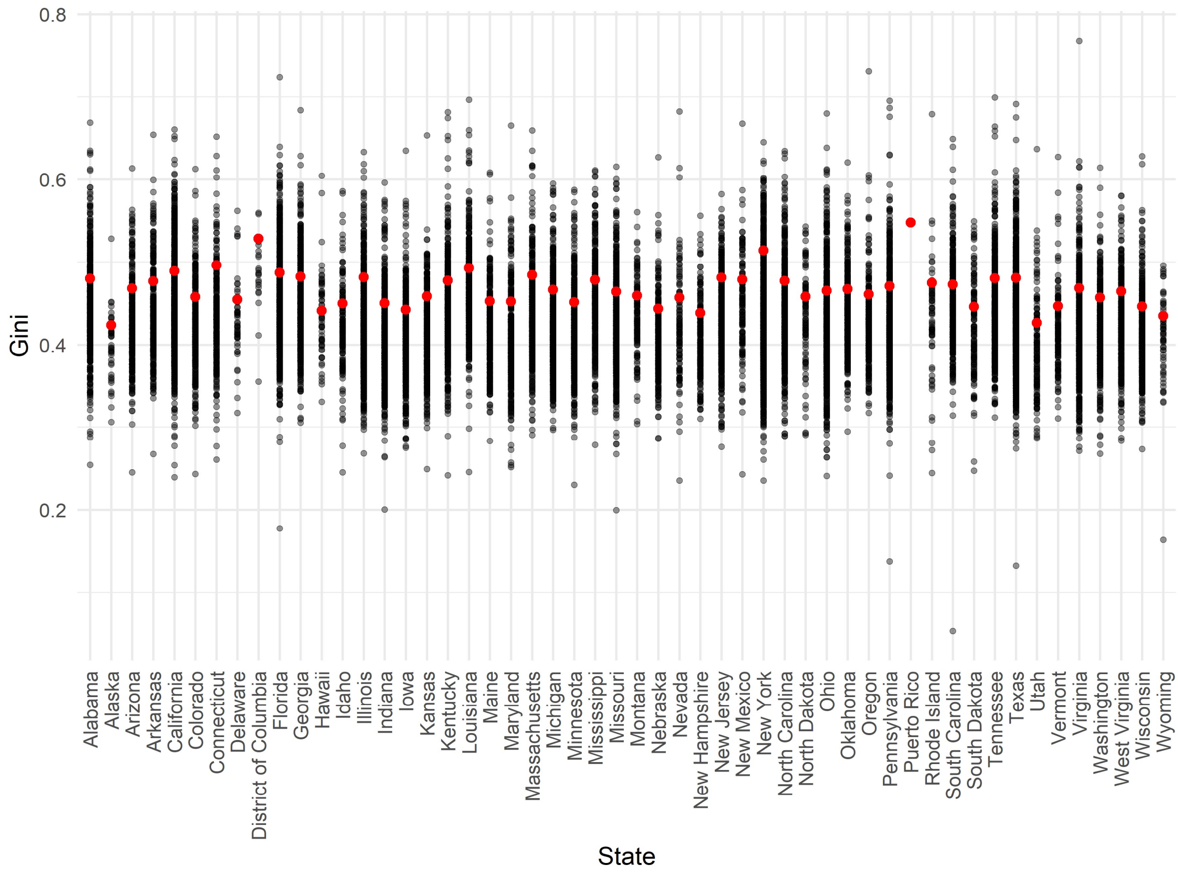
I first analyse tax data in the US on income and charitable donations at the ZIP-level (N = 133,870), and second Wave 8 of a large household survey of UK residents, Understanding Society (N = 39,289), which contains questions on recent charitable giving and granular, neighborhood-level geographical markers. Across both these samples, I find robust evidence of a positive relationship between local inequality and both the amount donated to charity conditional on having donated something (i.e. the intensive margin), and on the likelihood of donating at all (i.e. the extensive margin). The estimated effect is substantive – for the UK a two standard deviation increase in local inequality is associated with an expected increase in the odds of giving by over 12%, for example.

I also document significant interaction effects with income on the intensive margin in both the US and UK sample, as well as on the extensive margin in the US. In the US, the highest income group (over $200k in gross income), sees an expected 15% increase relative to the lowest income category ($25k or under). In order to mitigate endogeneity concerns stemming from selection effects – i.e. the possibility that higher-income, more pro-social individuals choose to live in areas of higher inequality – I restrict the UK sample to only those who live within a short distance (5 mile radius) of where they grew up (N = 2,312). The effect size grows larger when analysing this much smaller sample for both the intensive and extensive margins.

I then explore whether positive inter-class contact is driving these results by exploiting a module on social networks in Wave 6 of Understanding Society. The survey asks what proportion of friends have a similar income to the respondent. I show that local economic inequality increases the likelihood of having some friends with dissimilar incomes to oneself, and that having an economically diverse group of friends is an important predictor of charitable giving. However, this variable does not mediate the observed relationship between income and inequality for pro-social behaviour, suggesting that local inequality has a positive impact on giving beyond its effect on friendship networks.

In what follows I first detail the data and methodology in Section 4.2. Section 4.3 presents the results. And, finally, Section 4.4 concludes with a discussion of limitations and further research.

Figure 7: US State and ZIP-level income inequality, 2014-18



Note: The figure shows US state-level income inequality (red dot) and within-state ZIP-level income inequality (black dots). Inequality is measured using the Gini coefficient of incomes and obtained from the American Community Survey (Bureau, 2021).

4.2 Data and methodology

For the US, I test the interaction between inequality and income using data on charitable donations from tax returns provided by the US Internal Revenue Service (IRS, 2018). The data is disaggregated at the US ZIP-level and broken down by adjusted gross income bracket (6 groups in total: \$1-\$24,999; \$25,000-\$49,999; \$50,000-\$74,999; \$75,000-\$99,000; \$100,000-\$199,999;

$200,000+). This allows me to analyse variation in the extensive and intensive margins of charitable giving by income group and ZIP-code. In particular, I take the proportion of returns by income group which contain some charitable giving (M = 0.09), and the average amount donated per return conditional on some returns donating (M = $4,101, SD = $9,764). I obtain income inequality estimates from the American Community Survey (ACS) for the five year period 2014-2018 for every ZIP-code area with at least 1,000 residents (Bureau, 2021). ZIP-code areas have a mean population of 14,041 (SD = 15,846). As indicated in Figure 7, ZIP-level inequality is highly dispersed (M = 0.43, SD = 0.06, Max. = 0.77, Min. = 0.02).

To estimate the interaction effect, I use hierarchical linear modeling (via the `lme4` package in R; Bates et al. (2015)), with income groups nested within ZIP-code areas. I take the logistic functional form for the proportion of returns since it varies between 0 and 1, and I logarithmise the amount donated since the values are strictly positive. I include state fixed effects and control for a number of important ZIP-level variables: median income, population density (residents / squared mile), the proportion of the population that is White, has a university degree or above, is below the poverty line, is young (under 18 years old), and old (65 years old and over). Table A.6 in the Annex provides descriptive statistics for each of the variables used.

While there are advantages to using administrative tax data over surveys, in particular the data covers all tax returns, there are admittedly also some downsides. The income groups provided by IRS data are top coded and coarse, with individuals and households subsumed into income groups. The findings here might therefore be prone to the ecological fallacy (Kramer, 1983; Openshaw, 1984), whereby associations observed at the group level are different from that of individuals. Finally, poorer households are more likely to take the standard deduction rather than itemise charitable donations (Neumayr & Pennerstorfer, 2020), which means that charitable giving is likely to be under-reported for lower income groups. While there is no reason to suspect that this itemisation differential by income group varies by level of inequality, I cannot rule this out.

To provide further evidence regarding the relationship between income, local inequality and pro-social behaviour, and to verify that the results generalises outside the US, I turn to a large-scale survey of UK households matched with neighborhood-level inequality measures. In particular, I combine information on self-reported charitable giving in Wave 8 of Understanding Society (N =

39,289; gathered in 2016-17; University of Essex & Economic Research (2020)) with data on economic inequality at the neighborhood-level. Due to a lack of granular data on income or wealth (unlike the US, the UK does not gather this information as part of the decennial census), the UK inequality measures used here are based on housing values for around 23 million UK addresses (Suss, 2021). Neighborhoods are taken as the UK Middle Lower Super Output Area (MSOA) – census areas that are population weighted (M = 7,787, SD = 1,600) and meant to adhere to natural neighborhood boundaries.[19]

Understanding Society asks respondents whether they gave money to charitable organisations in the last 12 months (M = 0.66) and, if so, how much was given (M = £241, SD = £623). Survey respondents also report their gross monthly income (M = £48,750, SD = £34,954) and other information that allows me to account for individual differences. I control for age, gender, education, ethnicity, political orientation (proxied by reported political party support), religiosity, and marital status. I also control for other neighbourhood-level factors: median house prices and population density, and I include fixed effects for UK region (see Table A.7 for full descriptive statistics). As with the US data, I use multilevel modelling with individual respondents nested within MSOAs to test the interaction between income and MSOA-level inequality.

Wave 6 of Understanding Society (2014-2015) also contains a module on social support networks which allows me to investigate whether the relationship between inequality and pro-social behaviour is mediated by social contact between different economic groups in the form of friendships. In particular, the survey asks respondents "What proportion of your friends have similar incomes to you?" which I dichotomise such that 0 = "all similar" and 1 = "more than half", "about half" or "less than half." Given Understanding Society is a longitudinal study, I carry these responses forward for individual respondents which appear in both waves.

To examine whether economically diverse friendships mediate the relationship between local inequality and charitable giving, I first specify the same multilevel models used to analyse the

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[19] MSOAs are built up from lower level geographies, known as Output Areas, which are, according to the UK's Office for National Statistics "designed to … be as socially homogeneous as possible based on tenure of household and dwelling type" and "Urban/rural mixes were avoided where possible…[with] approximately regular shapes and tended to be constrained by obvious boundaries such as major roads. See further details on UK census geographies here: https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography.

Understanding Society sample but with the potential mediator as the outcome measure. I then simply compare the base models with and without the potential mediator as an additional control.

4.3 Results

4.3.1 Local inequality and charitable giving in the United States

Table 12 provides the standardised coefficients for the main effects of inequality and income group as well as the interaction between them. The analysis reveals a significant positive direct relationship between local inequality and the extensive margin, as well as a positive interaction between income and inequality at the ZIP-level for both the proportion of returns per group with some donation and the average amount donated. Notably, the effect on the average amount donated is concentrated in the highest income group ($\exp(\beta) = 1.21$, $p < 0.01$) with only moderately positive interaction terms or insignificant interaction terms for other income groups, and the lowest income category group has a negative, but substantively small, coefficient ($\exp(\beta) = 0.99$, $p < 0.05$). Moreover, the main effect of income is also significant for each category, with higher income groups expected to donate in higher proportion and in greater absolute amounts. These findings contrast with those of Côté et al. (2015). Indeed, the effect is in the opposite direction, with the relationship between income and giving depending positively on the level of local inequality, both for the extensive and intensive margins. The full regression table is reported in the Annex – see Table A.8.

In order to verify the robustness of these results, I run a number of checks. First, I alter the measure of inequality used. Rather than the Gini coefficient, I take the top 5% share of total income. Also, rather than using measures of inequality for 2014-2018, I use the Gini coefficients for each ZIP-code from 2007-2011 (the first 5-year window provided by the ACS at the ZIP-level). Inequality is moderately persistent over time (0.62). Second, I examine sub-samples of the data, running regressions for small ZIP-code areas (which I define as less than 50k total population) and large ZIP-code areas (over 50k) separately. All these robustness checks find the same pattern of results for the relationship between inequality and charitable giving and the interaction between income and inequality (see Table A.9).

I also examine whether the same interaction effect exists when income is interacted with state-level inequality, replicating the spatial unit utilised by Côté et al. (2015) and Schmukle et al. (2019) – see Table A.10. In contrast to Table 12, the interaction between income and inequality is negative and significant for the extensive margin and insignificant for the intensive margin, except for the largest income group, where the coefficient is positive and significant but much smaller in size ($\exp(\beta)$ = 1.06; $p < 0.05$. This underlines the importance of the chosen spatial unit of analysis. Inequality measured at an aggregated level reaches the opposite conclusion or largely fails to detect an effect when there is one at the more localised and contextually relevant ZIP-level.

I also verify the results using the county-level as the geographical unit of analysis. The same pattern of results is found as in Table 12 – see Table A.11.

Table 12: Regression results for US ZIP-level inequality

	Dependent variable:	
	Donated to charity	Average amount donated
	(1)	(2)
Inequality	0.175***	-0.008**
	(0.008)	(0.004)
37,500	1.367***	0.403***
	(0.002)	(0.004)
62,500	2.331***	0.555***
	(0.002)	(0.004)
87,500	2.759***	0.727***
	(0.002)	(0.004)
150,000	3.337***	1.101***
	(0.002)	(0.004)
200,000+	4.276***	1.986***
	(0.002)	(0.004)
Inequality:37,500	-0.032***	0.032***
	(0.002)	(0.004)
Inequality:62,500	-0.054***	0.045***
	(0.002)	(0.004)
Inequality:87,500	0.005***	0.023***
	(0.002)	(0.004)
Inequality:150,000	0.036***	-0.007*
	(0.002)	(0.004)
Inequality:200,000+	0.144***	0.188***
	(0.002)	(0.004)
State fixed effect	Y	Y
Random effect level	ZIP	ZIP
Controls included	Y	Y
Observations	128,101	78,732
Log Likelihood	-1,036,726.000	-20,646.750
Akaike Inf. Crit.	2,073,592.000	41,435.500
Note:	*p<0.1; **p<0.05; ***p<0.01	

4.3.2 Local inequality and charitable giving in the United Kingdom

Figure 8 provides the coefficient estimates for the extensive and intensive margins of charitable giving in the UK sample. The main effect of inequality on propensity to donate is positive and significant for both, suggesting that inequality increases the likelihood of donating (exp(β) = 1.062, $p < .01$) and the amount donated (exp(β) = 1.069, $p < .01$), irrespective of income.

Furthermore, the results indicate that there is a significant interaction between income and inequality for the amount given conditional on giving ($\exp(\beta) = 1.024$, $p < 0.01$), but not for the likelihood of giving ($\exp(\beta) = 1.007$, $p > 0.1$). See Table A.12 for full results.

To interpret the results, I plot the expected amount of charitable donations for those that reported donating in the previous 12 months as inequality is varied for different points in the income distribution (mean and +/- 1 standard deviation) – see Figure 9. One striking feature is apparent in the model describing the interaction between income and amount donated (Panel B of Figure 9). At very low levels of local inequality the amount donated is roughly similar for all income levels, but at high levels of inequality the amount donated is expected to be far larger for higher incomes.

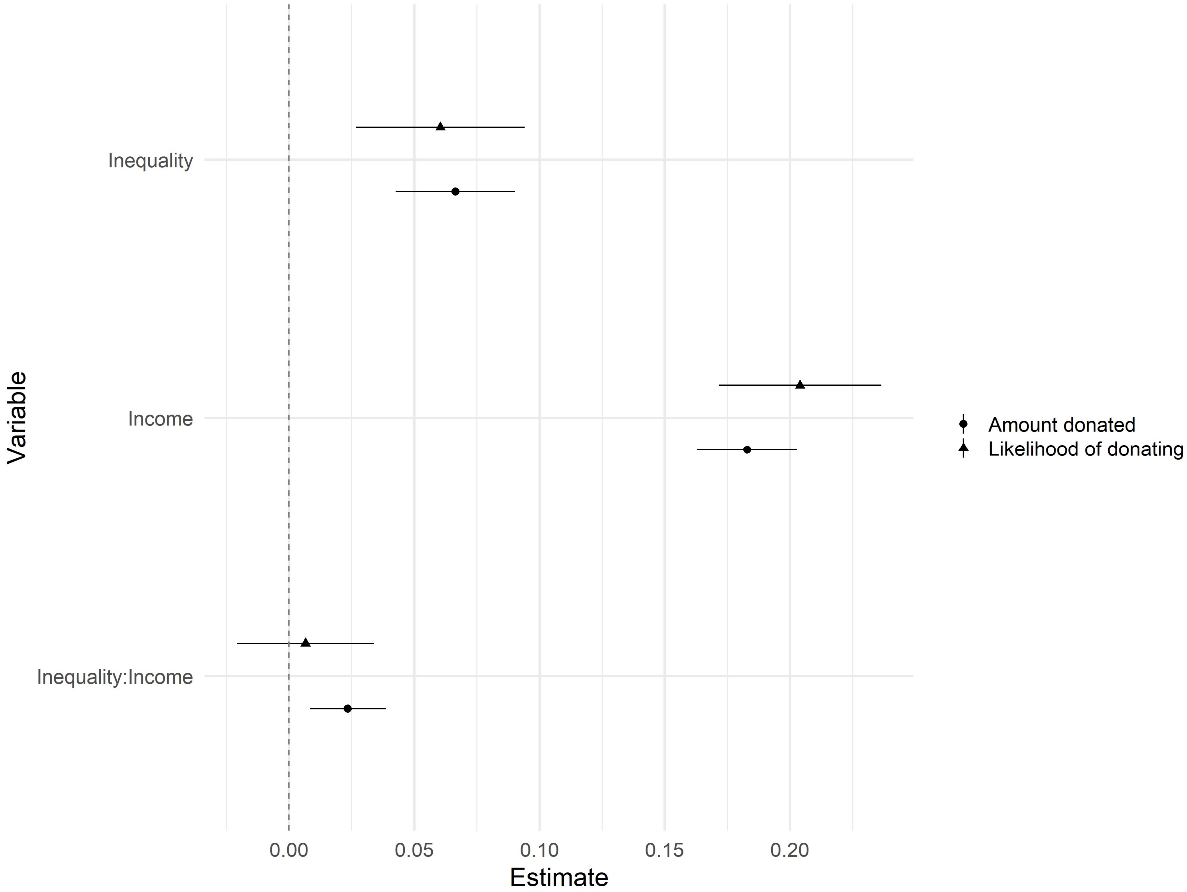
I verify that these results are robust in a number of ways. First, I check whether these results hold for alternative measure of inequality – rather than the Gini coefficient, I take the top 1% share measure. Second, rather than taking the absolute amount donated to charity, I instead use the percentage of income donated to charity as the outcome measure. The results are consistent – see Table A.13 and Table A.14.

I also check whether the relationship exists at different geographical levels of aggregation, both more granular and more aggregated than MSOAs. First, going more granular, I take the Lower Super Output Area (LSOA), which are constituent building blocks of MSOAs (population M = 1,471; SD = 428). The main effect and interaction effect remain significant and positive for the amount donated, and only the main inequality effect is significant for the likelihood of donating – see Table A.15. Second, I go up to the Local Authority District (LAD) level (population M = 161,138; SD = 109,066). The interaction is significant for both the likelihood of donating and amount given, albeit weaker statistically and substantively for the amount given ($\beta = 1.033$, $p < 0.1$), suggesting that some of the LADs are potentially too large such that the inequality measure is less contextually-relevant for individuals. See Table A.16 for these regression results.

Next, I check whether these results generalise to other pro-social behaviours. For this, I test whether inequality interacts with income when self-reported volunteering behaviour is the outcome measure. Once more, I look at both the extensive margin (whether volunteered in the last 12 months – M = 0.18) and intensive margins (hours spent volunteering in the last 4 weeks – M = 11.17, SD = 18.98). As with charitable giving, the main effect of local inequality is positive and significant for the likelihood of volunteering (β = 0.092, $p < 0.01$). For the hours volunteered, the main inequality effect is negative and significant (β = -0.038, $p < 0.05$) while the interaction term is positive and weakly significant (β = 0.023, $p < 0.1$), providing some evidence of a general interaction between income and inequality on pro-social behavior – see Table A.17.

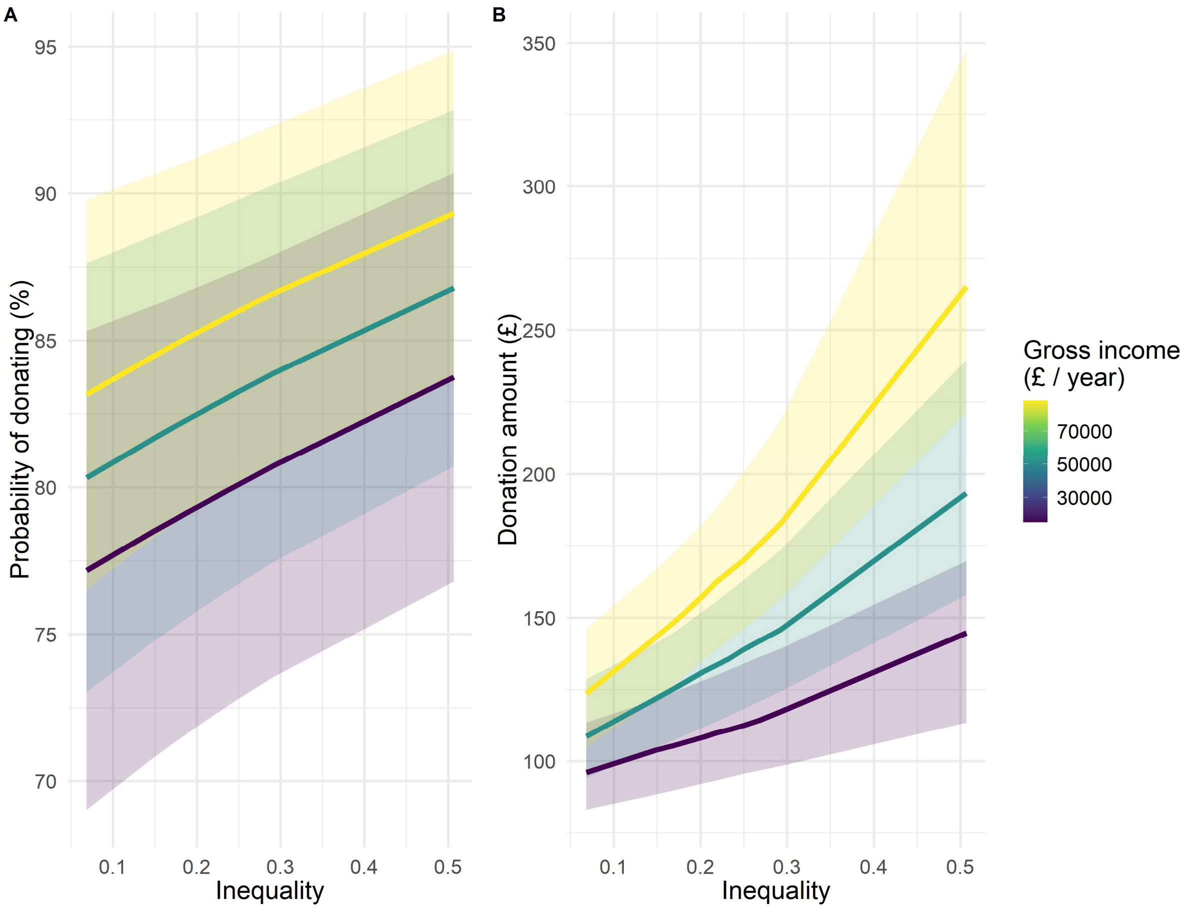
Lastly, in order to mitigate endogeneity concerns, I restrict the sample to those who live within a 5 mile radius of where they grew up. This reduces the sample dramatically (N = 2,958), but alleviates selection concerns, e.g. more generous and richer individuals choosing to live in areas that are also more unequal. The main inequality effect and interaction term for the amount donated remain statistically significant ($p < 0.05$) and are even more substantive when looking at the restricted sample (β = 0.146 and 0.076 respectively). However, the main effect on the likelihood of donating is statistically weaker (β = 0.113; $p < 0.1$ – see Table A.18).

Figure 8: Standardised and exponentiated coefficient plot for the interaction between UK MSOA-level inequality and income on charitable donations



Note: Regression models include MSOA-level random intercept, UK region fixed effects, and controls for age, gender, education, ethnicity, marital and employment status, political orientation, population density, median house price, and religiosity. N = 31,381 and 20,856 for the likelihood of donating and amount donated models respectively. See Table A.12 for full results. Error bands are 95% confidence intervals.

Figure 9: Interaction between inequality and income, UK data



Note: Income is set at its mean value and above and below one standard deviation from the mean. All other continuous variables are fixed at their median value, other explanatory variables are fixed as follows: female, White, with a degree, employed, married, religious, supporter of the Liberal Democrats. Standard errors are calculated using 99 bootstrapped simulations with 95% confidence intervals plotted.

4.3.3 Local inequality and friendship networks

I now turn to investigating the mechanism behind the positive inequality-income interaction. In particular, I test whether differential friendship networks in equal and unequal areas might be driving the results. Column 1 of Table 13 regresses whether the respondent reported at least some friends with dissimilar incomes on the full set of variables. As expected, local inequality affects social networks, with the odds of having economically diverse friendship group approximately 5% higher with a one standard deviation increase in neighbourhood inequality (*p*

< 0.05). Moreover, as Columns 2 and 3 demonstrate, having some friends with different incomes is an important factor affecting charitable giving, both in terms of the likelihood of donating and the amount donated. However, the friendship variable does not mediate the effect of inequality on giving, and the results for the main effect and interaction effect are roughly the same, albeit slightly weaker statistically and substantively.[20]

Table 13: Likelihood of having friends with dissimilar incomes

	Dependent variable:		
	Friends with dissimilar income?	Donated to charity?	Amount donated to charity
	(1)	(2)	(3)
Inequality	0.047**	0.036*	0.064***
	(0.022)	(0.019)	(0.013)
Income	0.065***	0.219***	0.199***
	(0.022)	(0.020)	(0.011)
Friends with dissimilar income		0.165***	0.218***
		(0.041)	(0.028)
Inequality : Income	0.014	0.006	0.018**
	(0.018)	(0.017)	(0.009)
Region fixed effect	Y	Y	Y
Random effect level	MSOA	MSOA	MSOA
Control variables	Y	Y	Y
Observations	26,261	24,560	17,053
Log Likelihood	-11,086.990	-13,913.860	-28,519.520
Akaike Inf. Crit.	22,227.980	27,883.720	57,097.030
Note:	*p<0.1; **p<0.05; ***p<0.01		

4.4 Discussion and conclusion

The results from this analysis are clear but contrary to what has been reported in a notable paper by Côté et al. (2015) on inequality and pro-social behaviour – I find robust evidence for a positive interaction between income and local inequality across two studies in the US and UK. Higher income individuals and households are generally more likely to donate and more generous in absolute terms when giving, and this effect is even larger in local contexts of high inequality for the average amount donated in the UK, and both the extensive and intensive

[20] I perform non-parametric causal mediation analysis (Imai et al., 2011) using the `mediation` package in R (Tingley et al., 2014) with 1,000 bootstrapped simulations (unreported).

margins in the US. Moreover, I find that the interaction between income and inequality generalises to volunteering. In explaining their findings, Côté et al. (2015) argue that higher inequality might trigger a sense of entitlement amongst richer individuals. The results here suggest that the opposite is the case when looking at more granular measures of inequality – it appears as though local inequality induces greater social solidarity.

The key contribution of this paper is to examine how local rather than macro manifestations of inequality interacts with income for pro-sociality. While national inequality has been the focus of scholars, the role of local contexts, both in shaping perceptions of national inequality (e.g. by providing distributional information that is generalised to wider society) and by altering attitudes and behaviour directly (e.g. by affecting the mix of people we frequently encounter and become friends with), has been less appreciated.

What explains the positive interaction between income and inequality? While the arguments above suggest a few possible mechanisms, the data available allows me to investigate whether research on inter-group contact (Allport et al., 1954; Pettigrew et al., 2011; Pettigrew & Tropp, 2006), operationalised here as contact between different income groups, provides one answer. While I find that local inequality is associated with an increase in the likelihood of having at least some friends with dissimilar incomes, and having an economically diverse social network is positively associated with charitable giving, the effect of local economic inequality is not mediated by this variable. This does not rule out that greater contact is a mechanism behind these findings, but that this might result in increased empathy and charitable giving via a route other than increased friendships (e.g. by casual encounters or observations of those relatively worse off). Another possible explanation for the positive interaction, one which I am unable to explore here, does not require greater empathy on the part of the rich, just a greater sense of responsibility. The observed effect might arise from the rich wanting to give back to society as a way of satisfying their conscience (Lloyd & Breeze, 2013) if they reside in local areas which is higher in inequality.

This paper is not without limitations. First, while the findings presented above are robust to different specifications and sub-sample analyses, they fall short of identifying causal relationships. The biggest concern is that the findings arise from possible selection effects, whereby individuals and households move to areas which are more aligned with their preferences with respect to inequality, and that these choices are also correlated with charitable giving. I mitigate this concern by exploiting information from Understanding Society on whether respondents live within 5 miles of where they were living as adolescents or upon first arrival to the UK. The restrictions do not change the results, but it is possible that the individuals that remain within a close distance of where they grew up are only those comfortable with the neighbourhood who didn't have reason to move. Since I cannot rule this out, I stop short of claiming that the observed relationships are causal.

One way that scholars have tried to identify the causal effect of economic inequality on individual pro-social behaviour is by conducting experiments in the lab or online (for example, Côté et al., 2015; McCall et al., 2017). However, it is unlikely that the artificial conditions and simplified representations of economic inequality within lab contexts adequately proxy for real-world experience (see also Schmukle et al., 2019 who make this same argument). Moreover, economic games, such as the canonical dictator game, which scholars have typically used to study pro-social preferences experimentally, have been shown to be poorly correlated with real-world pro-social behaviour (Galizzi & Navarro-Martínez, 2019). Therefore, in the absence of plausibly exogenous variation in economic inequality or a compelling instrumental variable, we have to rely on rigorously controlled observational data analysis to understand the effect of inequality on pro-social behaviour.

Future work might provide additional evidence to support the findings here. For example, while I analyse data from two separate countries, given importance of national culture and norms for pro-social behaviours (Einolf, 2017), future work could address whether the findings here generalise to other contexts and cultures. Indeed, while the US and UK differ in many respects, for example in terms of political institutions and tax treatment of charitable giving, they are also be relatively similar in other ways, notably in terms of high macro-inequality levels. Moreover, the rich and poor live cheek-by-jowl in many US and UK cities like New York and London, whereas other countries might tend towards greater economic segregation in urban settings. Future work might therefore expand the set of countries examined and also consider explicitly how local segregation moderates the relationship between inequality and pro-social behaviour.

The findings here suggest a positive implication of local economic inequality for pro-sociality. While it doesn't appear that greater friendships between rich and poor mediate the observed relationship, this is found to be an important determinant of charitable giving. Future work might therefore seek to shed further light on the mechanisms behind the positive interaction between local inequality and income for pro-sociality, perhaps by understanding how attitudes towards and reasons for charitable giving are affected by contextual economic discrepancies.

Overall, this paper provides evidence that, at least at the local level, rising inequality does not reinforce itself through reduced donations to charitable organisations. Instead, local inequality gives rise to increased generosity, in particular on the part of the relatively well-off.

4.5 Annex

Table A.6: Descriptive statistics for US data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Charity Volume	152,101	0.093	0.147	0.000	0.000	0.133	1.500
Charity amount (log scale)	157,347	2.727	3.734	0.000	0.000	4.800	16.193
Gini (ZIP)	133,870	0.429	0.055	0.053	0.393	0.462	0.768
Median income	133,762	61,410.360	25,638.160	9,570.000	44,672.000	71,439.000	250,001.000
Population	133,964	14,221.680	15,880.750	1,000.000	2,594.000	21,411.000	122,814.000
Population density (log scale)	133,964	0.661	2.237	0.0001	0.016	0.523	58.905
White (%)	133,964	0.812	0.203	0.000	0.737	0.958	1.000
Poor (%)	133,916	0.051	0.032	0.000	0.028	0.067	0.436
College degress (%)	133,964	0.184	0.117	0.000	0.101	0.234	0.859
Age 65+ (%)	133,964	0.174	0.065	0.000	0.134	0.203	0.878
Age less than 18 (%)	133,964	0.222	0.053	0.000	0.192	0.253	0.478

Table A.7: Descriptive statistics for UK data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Charity given	34,826	0.662	0.473	0.000	0.000	1.000	1.000
Charity amount	22,778	241.071	622.201	0.000	30.000	200.000	9,997.000
Gini (MSOA)	36,715	0.220	0.056	0.068	0.180	0.258	0.507
Income	38,769	48,750.340	34,954.140	0.000	24,349.920	64,058.040	1,032,787.000
Age	39,275	48.778	18.735	16.000	34.000	63.000	102.000
Female	39,289	0.544	0.498	0	0	1	1
Degree	38,431	0.383	0.486	0.000	0.000	1.000	1.000
White	38,970	0.808	0.394	0.000	1.000	1.000	1.000
Employed	37,535	0.567	0.496	0.000	0.000	1.000	1.000
Married	37,507	0.530	0.499	0.000	0.000	1.000	1.000
Religious	37,509	0.543	0.498	0.000	0.000	1.000	1.000
Population density	36,724	34.764	36.656	0.020	6.700	47.200	247.200
Median house value (MSOA)	36,715	251,370.900	150,880.600	52,997.810	140,974.100	322,997.500	2,197,955.000

Table A.8: Full multilevel regression results, US ZIP-level inequality

	Dependent variable:			
	Proportion donated		Donation amount	
	(1)	(2)	(3)	(4)
Inequality	0.194***	0.175***	0.035***	-0.008**
	(0.008)	(0.008)	(0.002)	(0.004)
37,500	1.365***	1.367***	0.405***	0.403***
	(0.002)	(0.002)	(0.004)	(0.004)
62,500	2.329***	2.331***	0.556***	0.555***
	(0.002)	(0.002)	(0.004)	(0.004)
87,500	2.760***	2.759***	0.729***	0.727***
	(0.002)	(0.002)	(0.004)	(0.004)
150,000	3.341***	3.337***	1.104***	1.101***
	(0.002)	(0.002)	(0.004)	(0.004)
200,000+	4.318***	4.276***	1.992***	1.986***
	(0.002)	(0.002)	(0.004)	(0.004)
Median income	0.611***	0.612***	-0.091***	-0.091***
	(0.010)	(0.010)	(0.003)	(0.003)
Ln(Population)	-0.013*	-0.016**	0.008***	0.008***
	(0.008)	(0.008)	(0.003)	(0.003)
White (%)	0.020	0.016	-0.099***	-0.099***
	(0.017)	(0.017)	(0.005)	(0.005)
Poor (%)	0.171***	0.174***	-0.009**	-0.011***
	(0.013)	(0.013)	(0.004)	(0.004)
25+ with college degree (%)	-0.188***	-0.191***	-0.014***	-0.016***
	(0.014)	(0.014)	(0.004)	(0.004)
Age 65+ (%)	0.322***	0.324***	0.017***	0.018***
	(0.014)	(0.014)	(0.004)	(0.004)
Age less than 18 (%)	0.059***	0.064***	0.075***	0.078***
	(0.016)	(0.016)	(0.005)	(0.005)
Inequality:37,500		-0.032***		0.032***
		(0.002)		(0.004)
Inequality:62,500		-0.054***		0.045***
		(0.002)		(0.004)
Inequality:87,500		0.005***		0.023***
		(0.002)		(0.004)
Inequality:150,000		0.036***		-0.007*
		(0.002)		(0.004)
Inequality:200,000+		0.144***		0.188***
		(0.002)		(0.004)
Constant	-4.858***	-4.852***	1.339***	1.343***
	(0.043)	(0.043)	(0.013)	(0.013)
State fixed effect	Y	Y	Y	Y
Random effect level	ZIP-code	ZIP-code	ZIP-code	ZIP-code
Observations	128,101	128,101	78,732	78,732
Log Likelihood	-1,054,945.000	-1,036,726.000	-22,685.120	-20,646.750
Akaike Inf. Crit.	2,110,020.000	2,073,592.000	45,502.240	41,435.500
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A.9: Robustness checks, US ZIP-level inequality

	Dependent variable:							
	Top 5% concentration	Top 5% concentration	Gini 2007-2011	Gini 2007-2011	Population < 50k	Population < 50k	Population >= 50k	Population >= 50k
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inequality	0.169***	-0.023***	0.172***	-0.005	0.176***	-0.009**	0.035**	0.042***
	(0.007)	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.017)	(0.015)
37,500	1.370***	0.404***	1.369***	0.403***	1.366***	0.398***	1.376***	0.477***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.010)
62,500	2.335***	0.555***	2.334***	0.555***	2.313***	0.552***	2.405***	0.598***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.010)
87,500	2.765***	0.727***	2.761***	0.727***	2.714***	0.727***	2.954***	0.730***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.010)
150,000	3.342***	1.102***	3.339***	1.101***	3.291***	1.105***	3.544***	1.028***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.010)
200,000+	4.276***	1.983***	4.273***	1.984***	4.240***	1.993***	4.446***	1.889***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.011)
Median income	0.586***	-0.093***	0.595***	-0.093***	0.628***	-0.089***	0.140***	-0.040**
	(0.009)	(0.003)	(0.010)	(0.003)	(0.010)	(0.003)	(0.026)	(0.019)
Ln(Population)	-0.013*	0.006**	-0.020**	0.007***	0.015*	0.006**	-0.102***	0.004
	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.016)	(0.004)
White (%)	-0.003	-0.101***	0.007	-0.102***	-0.020	-0.125***	-0.114***	-0.061***
	(0.016)	(0.005)	(0.017)	(0.005)	(0.018)	(0.006)	(0.012)	(0.006)
Poor (%)	0.218***	0.004	0.182***	-0.015***	0.164***	-0.015***	-0.143***	0.001
	(0.012)	(0.004)	(0.013)	(0.004)	(0.013)	(0.005)	(0.023)	(0.009)
25+ with college degree (%)	-0.147***	-0.008*	-0.180***	-0.018***	-0.205***	-0.025***	-0.016	-0.018**
	(0.013)	(0.004)	(0.014)	(0.004)	(0.014)	(0.005)	(0.021)	(0.009)
Age 65+ (%)	0.309***	0.017***	0.327***	0.019***	0.315***	0.028***	0.060***	0.009
	(0.014)	(0.004)	(0.014)	(0.004)	(0.015)	(0.005)	(0.011)	(0.006)
Age less than 18 (%)	0.015	0.066***	0.060***	0.085***	0.152***	0.110***	0.086***	0.061***
	(0.015)	(0.004)	(0.016)	(0.005)	(0.016)	(0.006)	(0.014)	(0.008)
Inequality:37,500	-0.071***	0.027***	-0.045***	0.032***	-0.035***	0.033***	-0.009**	0.028**
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.012)
Inequality:62,500	-0.111***	0.040***	-0.071***	0.047***	-0.061***	0.046***	0.002	0.034***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.012)
Inequality:87,500	-0.065***	0.026***	-0.015***	0.026***	-0.004**	0.024***	0.079***	0.001
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.012)
Inequality:150,000	-0.028***	0.007*	0.021***	-0.005	0.027***	-0.005	0.107***	-0.029**
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.012)
Inequality:200,000+	0.118***	0.195***	0.125***	0.204***	0.139***	0.191***	0.182***	0.139***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.012)
Constant	-4.797***	1.344***	-4.855***	1.338***	-4.849***	1.341***	-4.587***	1.403***
	(0.042)	(0.013)	(0.043)	(0.013)	(0.044)	(0.013)	(0.162)	(0.105)
State fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Random effect level	ZIP-code	ZIP-code	ZIP-code	ZIP-code	ZIP-code	ZIP-code	ZIP-code	ZIP-code
Observations	124,802	78,220	128,101	78,732	122,712	73,391	5,389	5,341
Log Likelihood	-1,017,460.000	-20,209.970	-1,035,115.000	-20,178.920	-964,430.600	-20,078.200	-64,955.920	-227.801
Akaike Inf. Crit.	2,035,060.000	40,561.940	2,070,370.000	40,499.830	1,929,001.000	40,298.400	130,031.800	577.602
Note:	*p<0.1; **p<0.05; ***p<0.01							

Table A.10: Full multilevel regression results, US state-level inequality

	Dependent variable:			
	Proportion donated		Donation amount	
	(1)	(2)	(3)	(4)
Inequality	-0.001	0.058	-0.014	-0.042
	(0.086)	(0.087)	(0.056)	(0.059)
17,500	0.789***	0.852***	0.654***	0.654***
	(0.003)	(0.004)	(0.030)	(0.030)
37,500	1.804***	1.835***	1.033***	1.033***
	(0.003)	(0.004)	(0.030)	(0.030)
62,500	2.782***	2.816***	1.144***	1.144***
	(0.003)	(0.003)	(0.030)	(0.030)
87,500	3.276***	3.290***	1.283***	1.283***
	(0.003)	(0.003)	(0.030)	(0.030)
150,000	3.892***	3.915***	1.609***	1.609***
	(0.003)	(0.003)	(0.030)	(0.030)
200,000+	5.015***	5.077***	2.947***	2.947***
	(0.003)	(0.003)	(0.030)	(0.030)
Median income	0.010	0.010	-0.234***	-0.234***
	(0.128)	(0.128)	(0.082)	(0.082)
Ln(Population)	0.111**	0.111**	-0.030	-0.030
	(0.044)	(0.044)	(0.028)	(0.028)
White (%)	-0.194***	-0.195***	-0.065**	-0.065**
	(0.051)	(0.051)	(0.033)	(0.033)
Poor (%)	0.077	0.078	-0.019	-0.019
	(0.114)	(0.115)	(0.074)	(0.074)
25+ with college degree (%)	0.346***	0.347***	0.042	0.041
	(0.077)	(0.077)	(0.053)	(0.053)
Age 65+ (%)	0.157**	0.159**	-0.104**	-0.104**
	(0.068)	(0.068)	(0.043)	(0.043)
Age less than 18 (%)	0.243***	0.245***	0.024	0.024
	(0.079)	(0.079)	(0.050)	(0.050)
Religious (%)	-0.048	-0.048	0.035	0.035
	(0.046)	(0.046)	(0.029)	(0.029)
GOP support (%)	-0.00002	-0.00002	0.037	0.036
	(0.001)	(0.001)	(0.028)	(0.028)
Inequality:17,500		-0.118***		0.049
		(0.004)		(0.030)
Inequality:37,500		-0.059***		0.058*
		(0.003)		(0.030)
Inequality:62,500		-0.064***		0.049
		(0.003)		(0.030)
Inequality:87,500		-0.024***		0.019
		(0.003)		(0.030)
Inequality:150,000		-0.042***		-0.036
		(0.003)		(0.030)
Inequality:200,000+		-0.111***		0.062**
		(0.003)		(0.030)
Constant	-5.254***	-5.286***	0.435***	0.435***
	(0.032)	(0.032)	(0.028)	(0.028)

Random effect level	State	State	State	State
Observations	364	364	364	364
Log Likelihood	-104,678.100	-100,431.900	78.728	70.647
Akaike Inf. Crit.	209,392.100	200,911.900	-119.456	-91.293
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A.11: Full multilevel regression results, US county-level inequality

	Dependent variable:			
	Proportion donated		Donation amount	
	(1)	(2)	(3)	(4)
Inequality	0.026***	0.053***	0.005	-0.042***
	(0.008)	(0.008)	(0.005)	(0.009)
17,500	0.782***	0.842***	0.583***	0.579***
	(0.003)	(0.004)	(0.010)	(0.010)
37,500	1.791***	1.813***	0.961***	0.956***
	(0.003)	(0.003)	(0.010)	(0.009)
62,500	2.766***	2.791***	1.151***	1.147***
	(0.003)	(0.003)	(0.009)	(0.009)
87,500	3.259***	3.263***	1.333***	1.329***
	(0.003)	(0.003)	(0.010)	(0.010)
150,000	3.857***	3.867***	1.690***	1.685***
	(0.003)	(0.003)	(0.009)	(0.009)
200,000+	4.945***	4.943***	2.601***	2.597***
	(0.003)	(0.003)	(0.010)	(0.009)
Median income	0.138***	0.141***	-0.120***	-0.121***
	(0.014)	(0.014)	(0.008)	(0.008)
Ln(Population)	0.184***	0.184***	-0.038***	-0.038***
	(0.009)	(0.009)	(0.005)	(0.005)
White (%)	-0.130***	-0.130***	-0.087***	-0.086***
	(0.010)	(0.010)	(0.006)	(0.006)
Poor (%)	-0.072***	-0.071***	-0.012*	-0.013*
	(0.012)	(0.012)	(0.007)	(0.007)
25+ with college degree (%)	0.059***	0.058***	0.053***	0.053***
	(0.011)	(0.011)	(0.007)	(0.007)
Age 65+ (%)	0.075***	0.075***	-0.031***	-0.030***
	(0.008)	(0.008)	(0.005)	(0.005)
Age less than 18 (%)	-0.029***	-0.029***	0.025***	0.025***
	(0.009)	(0.009)	(0.005)	(0.005)
Religious (%)	0.005	0.005	0.026***	0.026***
	(0.007)	(0.007)	(0.004)	(0.004)
GOP support (%)	-0.081***	-0.082***	0.104***	0.104***
	(0.010)	(0.010)	(0.006)	(0.006)
Inequality:17,500		-0.113***		0.035***
		(0.003)		(0.010)
Inequality:37,500		-0.043***		0.047***

		(0.003)		(0.010)
Inequality:62,500		-0.050***		0.056***
		(0.003)		(0.010)
Inequality:87,500		-0.004		0.046***
		(0.003)		(0.010)
Inequality:150,000		-0.018***		0.022**
		(0.003)		(0.009)
Inequality:200,000+		0.0005		0.096***
		(0.003)		(0.010)
Constant	-5.407***	-5.418***	0.666***	0.671***
	(0.035)	(0.035)	(0.021)	(0.021)
State fixed effect	Y	Y	Y	Y
Random effect level	County	County	County	County
Observations	21,632	21,632	15,735	15,735
Log Likelihood	-302,815.400	-299,582.700	-1,283.499	-1,222.901
Akaike Inf. Crit.	605,766.700	599,313.300	2,704.998	2,595.801
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A.12: Full multilevel regression results, UK MSOA-level inequality

	Dependent variable:	
	Donated to charity?	Amount donated to charity (£)
	(1)	(2)
Inequality	0.060^{***}	0.067^{***}
	(0.017)	(0.012)
Income (£/year)	0.204^{***}	0.183^{***}
	(0.017)	(0.010)
Age	0.021^{***}	0.021^{***}
	(0.001)	(0.001)
Male	-0.316^{***}	0.098^{***}
	(0.026)	(0.018)
Degree	0.564^{***}	0.494^{***}
	(0.029)	(0.019)
White	0.259^{***}	-0.130^{***}
	(0.044)	(0.032)
Employed	0.322^{***}	0.208^{***}
	(0.030)	(0.022)
Married	0.165^{***}	0.121^{***}
	(0.029)	(0.020)
Religious	0.357^{***}	0.345^{***}
	(0.029)	(0.020)
Labour	-0.094^{***}	-0.047^{**}
	(0.036)	(0.024)
Liberal Democrat	0.121^{**}	0.171^{***}
	(0.061)	(0.036)
Other political party	-0.346^{***}	-0.147^{***}
	(0.037)	(0.026)
Population density	0.0002	0.002^{***}
	(0.001)	(0.0004)
Median house value	0.152^{***}	0.088^{***}
	(0.027)	(0.017)
Inequality:Income	0.007	0.024^{***}
	(0.014)	(0.008)
Constant	-0.703^{***}	2.728^{***}
	(0.107)	(0.078)
Region fixed effect	Y	Y
Random effect level	MSOA	MSOA
Observations	31,381	20,856
Log Likelihood	-18,228.630	-35,033.820
Akaike Inf. Crit.	36,511.270	70,123.640
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.13: Top 1% inequality regression, UK MSOA-level inequality

	Dependent variable:	
	Donated to charity?	Amount donated to charity
	(1)	(2)
Top 1% Inequality	0.040**	0.050***
	(0.016)	(0.011)
Income (£/year)	0.205***	0.184***
	(0.017)	(0.010)
Age	0.021***	0.021***
	(0.001)	(0.001)
Male	-0.316***	0.098***
	(0.026)	(0.018)
Degree	0.566***	0.497***
	(0.029)	(0.019)
White	0.262***	-0.124***
	(0.044)	(0.032)
Employed	0.320***	0.206***
	(0.030)	(0.022)
Married	0.164***	0.121***
	(0.029)	(0.020)
Religious	0.357***	0.345***
	(0.029)	(0.020)
Labour	-0.093***	-0.045*
	(0.036)	(0.024)
Liberal Democrat	0.122**	0.173***
	(0.061)	(0.036)
Other political party	-0.345***	-0.146***
	(0.037)	(0.026)
Population density	0.0001	0.002***
	(0.001)	(0.0004)
Median house value	0.174***	0.108***
	(0.025)	(0.016)
Top 1% Inequality:Income	0.002	0.023***
	(0.014)	(0.008)
Constant	-0.672***	2.751***
	(0.106)	(0.078)
Region fixed effect	Y	Y
Random effect level	MSOA	MSOA
Observations	31,381	20,857
Log Likelihood	-18,231.950	-35,041.700
Akaike Inf. Crit.	36,517.900	70,139.400
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.14: Charitable donation (%), UK MSOA-level inequality

	Dependent variable:	
	Donated to charity?	Amount donated to charity
	(1)	(2)
Inequality	0.074***	0.071***
	(0.012)	(0.012)
Income (£/year)	-0.361***	-0.365***
	(0.010)	(0.010)
Age	0.024***	0.024***
	(0.001)	(0.001)
Male	0.088***	0.088***
	(0.018)	(0.018)
Degree	0.461***	0.461***
	(0.020)	(0.020)
White	-0.147***	-0.151***
	(0.032)	(0.033)
Employed	0.081***	0.081***
	(0.022)	(0.022)
Married	-0.041**	-0.042**
	(0.020)	(0.020)
Religious	0.350***	0.350***
	(0.020)	(0.020)
Labour	-0.053**	-0.053**
	(0.024)	(0.024)
Liberal Democrat	0.159***	0.159***
	(0.037)	(0.037)
Other political party	-0.135***	-0.135***
	(0.026)	(0.026)
Population density	0.003***	0.003***
	(0.0004)	(0.0004)
Median house value	0.096***	0.093***
	(0.018)	(0.018)
Inequality:Income		0.023***
		(0.008)
Constant	-7.809***	-7.806***
	(0.080)	(0.080)
Region fixed effect	Y	Y
Random effect level	MSOA	MSOA
Observations	20,857	20,857
Log Likelihood	-35,498.650	-35,498.480
Akaike Inf. Crit.	71,051.290	71,052.970
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.16: UK LSOA and Local Authority District level regression

	Dependent variable:			
	Donated to charity?	Amount donated to charity	Donated to charity?	Amount donated to charity
	(1)	(2)	(3)	(4)
Inequality	0.063***	0.055***	0.004	0.032*
	(0.016)	(0.011)	(0.023)	(0.017)
Income (£/year)	0.203***	0.178***	0.223***	0.201***
	(0.017)	(0.011)	(0.016)	(0.010)
Age	0.020***	0.021***	0.020***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.321***	0.096***	-0.308***	0.093***
	(0.026)	(0.018)	(0.026)	(0.019)
Degree	0.553***	0.476***	0.599***	0.536***
	(0.030)	(0.019)	(0.029)	(0.020)
White	0.265***	-0.144***	0.317***	-0.133***
	(0.045)	(0.032)	(0.042)	(0.031)
Employed	0.326***	0.214***	0.313***	0.180***
	(0.030)	(0.022)	(0.030)	(0.023)
Married	0.169***	0.127***	0.165***	0.125***
	(0.029)	(0.020)	(0.029)	(0.020)
Religious	0.363***	0.339***	0.357***	0.333***
	(0.030)	(0.020)	(0.029)	(0.020)
Labour	-0.086**	-0.041*	-0.110***	-0.053**
	(0.037)	(0.024)	(0.036)	(0.024)
Liberal Democrat	0.120*	0.162***	0.131**	0.176***
	(0.063)	(0.036)	(0.062)	(0.038)
Other political party	-0.336***	-0.143***	-0.354***	-0.159***
	(0.038)	(0.026)	(0.037)	(0.027)
Population density	0.0002	0.002***	-0.001	0.003***
	(0.0004)	(0.0003)	(0.001)	(0.001)
Median house value	0.167***	0.126***	0.099**	0.020
	(0.024)	(0.014)	(0.041)	(0.029)
Inequality:Income	0.007	0.025***	0.042***	0.016*
	(0.015)	(0.008)	(0.014)	(0.009)
Constant	-0.693***	2.760***	-0.676***	2.692***
	(0.106)	(0.076)	(0.132)	(0.097)
Region fixed effect	Y	Y	Y	Y
Random effect level	LSOA	LSOA	LAD	LAD
Observations	31,366	20,847	29,691	19,693
Log Likelihood	-18,162.930	-34,903.460	-17,355.310	-33,151.070
Akaike Inf. Crit.	36,379.860	69,862.920	34,764.620	66,358.150
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A.17: Volunteering regression, UK MSOA-level inequality

	Dependent variable:			
	Volunteered?	Volunteered?	Number of hours volunteered	Number of hours volunteered
	(1)	(2)	(3)	(4)
Inequality	0.090***	0.092***	-0.034*	-0.038**
	(0.019)	(0.019)	(0.018)	(0.018)
Income (£/year)	-0.006***	-0.006***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.032	-0.032	0.068**	0.068**
	(0.029)	(0.029)	(0.030)	(0.030)
Male	0.676***	0.676***	0.040	0.041
	(0.031)	(0.031)	(0.032)	(0.032)
Degree	0.327***	0.329***	0.002	0.002
	(0.050)	(0.050)	(0.052)	(0.052)
White	-0.488***	-0.488***	-0.253***	-0.251***
	(0.034)	(0.034)	(0.034)	(0.034)
Employed	-0.014	-0.014	-0.066*	-0.064*
	(0.032)	(0.032)	(0.034)	(0.034)
Married	0.429***	0.429***	0.008	0.009
	(0.032)	(0.032)	(0.033)	(0.033)
Religious	-0.045	-0.045	0.064	0.064
	(0.039)	(0.039)	(0.039)	(0.039)
Labour	0.299***	0.298***	0.083	0.083
	(0.057)	(0.057)	(0.053)	(0.053)
Liberal Democrat	-0.093**	-0.094**	0.140***	0.138***
	(0.042)	(0.042)	(0.043)	(0.043)
Other political party	0.108***	0.110***	-0.037**	-0.048***
	(0.015)	(0.016)	(0.016)	(0.017)
Population density	-0.001*	-0.001*	-0.0003	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)
Median house value	0.169***	0.170***	-0.013	-0.015
	(0.026)	(0.026)	(0.024)	(0.024)
Inequality:Income		-0.010		0.023*
		(0.012)		(0.013)
Constant	-1.569***	-1.570***	2.134***	2.139***
	(0.120)	(0.120)	(0.121)	(0.121)
Region fixed effect	Y	Y	Y	Y
Random effect level	MSOA	MSOA	MSOA	MSOA
Observations	33,692	33,692	4,706	4,706
Log Likelihood	-15,455.560	-15,455.180	-6,787.869	-6,789.724
Akaike Inf. Crit.	30,963.120	30,964.360	13,629.740	13,635.450
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A.18: Restricted sample regression, respondents living within 5 miles of where they grew up, UK MSOA-level inequality

	Dependent variable:	
	Donated to charity?	Amount donated to charity
	(1)	(2)
Inequality	0.113*	0.146***
	(0.064)	(0.048)
Income (£/year)	0.191***	0.224***
	(0.069)	(0.044)
Age	0.013***	0.013***
	(0.004)	(0.003)
Male	-0.136	0.092
	(0.108)	(0.081)
Degree	0.519***	0.152*
	(0.115)	(0.085)
White	0.140	-0.310***
	(0.146)	(0.111)
Employed	0.451***	0.167*
	(0.114)	(0.090)
Married	0.378***	0.413***
	(0.114)	(0.089)
Religious	0.315**	0.519***
	(0.140)	(0.113)
Labour	-0.031	-0.189
	(0.163)	(0.116)
Liberal Democrat	0.086	-0.119
	(0.347)	(0.224)
Other political party	-0.360**	-0.103
	(0.183)	(0.138)
Population density	0.002	0.001
	(0.001)	(0.001)
Median house value	0.039	-0.026
	(0.091)	(0.068)
Inequality:Income	0.050	0.076***
	(0.052)	(0.024)
Constant	-0.623	3.328***
	(0.610)	(0.457)
Region fixed effect	Y	Y
Random effect level	MSOA	MSOA
Observations	1,758	1,044
Log Likelihood	-1,112.673	-1,740.020
Akaike Inf. Crit.	2,279.347	3,536.040
Note:	*p<0.1; **p<0.05; ***p<0.01	

5 Economic inequality and the spatial distribution of police stops and searches: evidence from London

Abstract: *We study the spatial distribution of stops and searches (S&S) in London in 2019. We hypothesise that – based on the interpretation of S&S as a tool of social control – economic inequality plays a role, with more unequal locations seeing higher volumes of stops. Using unique data on salient, spatially-granular economic inequality at the Lower Super Output Area (LSOA), we assess the relationship between inequality and the spatial concentration of searches. Results suggest a substantive positive association, even taking into account spatial effects, lagged crime rates and ethnic diversity. We also find that the effect of inequality depends on the level of affluence – the better off a location is, the stronger the effect of inequality on police stops and searches.*

5.1 Introduction

Police powers to stop and search (S&S) members of the public remain controversial. With the promise of deterring crime, police organisations around the world are legally authorised to stop citizens, check their identities, and search their possessions (Weber & Bowling, 2014). On the one hand, S&S powers premise on the idea of repressing criminal behaviour and thus ensuring that all members of the public feel safe, but at the same time they reproduce social inequality and the dominance of some groups over others (Bradford & Loader, 2016; Delsol & Shiner, 2015). In England and Wales, S&S has been more or less used continuously since the 1980s – with lively reactions from the public whenever its use increases.

Despite claims that such practices have some impact on crime, previous work has shown that this policy tends to be, at best, only slightly successful and overall a very ineffective tool for controlling offending behaviour (MacDonald et al., 2016; McCandless et al., 2016; Tiratelli et al., 2018). Moreover, S&S also comes with high costs, especially in terms of damages to police trustworthiness and legitimacy (Bradford, 2015, 2017). Given this apparent inefficacy as a crime-control strategy, previous work has suggested that the persistence of governmental reliance on S&S practices is more related to social order maintenance than to crime-fighting (Bradford & Loader, 2016; Tiratelli et al., 2018). Our goal is to further investigate aspects of this claim, particularly in terms of the spatial distribution in the use of S&S powers. With the focus on London, UK, in 2019, we ask where in the city stops and searches are mostly concentrated and demonstrate that the the spatial heterogeneity of this type of police resource allocation helps reveal parts of the mechanisms of S&S as a tool of social control (Bradford & Loader, 2016; Choongh, 1998).

Stop and search as a tool of social control is particularly expressed by the well documented literature on ethnic disproportionality (Bowling & Phillips, 2007; Quinton, 2015). Previous research has extensively demonstrated that Black, Asian, and Minority Ethnic (BAME) are disproportionately targeted by S&S practices when compared to overall demographics (Shiner et al., 2018). A common explanation for this disparity raises the issue of contextual circumstances that make some people "available" to be stopped and searched (see Philip AJ Waddington et al., 2004) – suggesting that the comparisons should not be made with the overall population, but with the "available population" – although this argument is based on a "self-fulfilling methodology" (Bridges, 2015). After all, "street availability is influenced by police decisions where and when to do stops and searches, and these decisions heavily influence the people that are 'available' to be stopped and searched" (EHRC, 2010, p. 57).

Building on this discussion, our focus is on *where* in London police officers decide to stop and search members of the public, rather than *whom* they stop and search. To do so, we use data at the level of Lower Super Output Areas (LSOAs) in 2019. We hypothesise that, if S&S is indeed a tool of social control, the spatial distribution of S&S practices would reveal the filtering out of some locations. In particular, we expect that areas marked by economic discrepancies would see heightened S&S activity. We therefore draw on a novel measure of salient, spatially-granular economic inequality developed by Suss (2021), demonstrating that local inequality is directly associated with a higher volume of S&S – locations where the economically deprived and the well-off co-exist are the areas where police S&S activity is most common – even when previous crime rates are taken into account.

The paper proceeds as follows. First, we set the scene and explain the legal context of S&S powers in England and Wales, review the studies that estimate the deterrent effect of S&S on crime rates, and discuss S&S as a tool of social control and the extent to which a focus on spatial patterns could contribute to the literature. Then we go on to present this study's data, methods, and results, and finish with a discussion on the spatial concentration of S&S practices in London.

5.2 Literature

5.2.1 Stop and search in England and Wales

Police officers acting with suspicion against citizens might be one of the oldest practices involved in policing activities. In the UK, police powers to stop and search members of the public are currently regulated by various pieces of legislation, but the Police and Criminal Evidence Act 1984 (PACE) is probably the most significant (Bridges, 2015). PACE established legal powers of the police to stop and search a person (or vehicle) in a public space as long as officers have reasonable suspicion that the person is in possession of stolen goods, weapons, or other prohibited articles. More recent developments in the legislation have granted further powers to the police, allowing for 'suspicion-less' stop and searches under specific circumstances; notably, section 60 of the Criminal Justice and Public Order Act 1994 (hereafter s60), which allows senior police officers to authorise stop and search practices against any person in a particular locality for 24 hours (which can be extended) with the goal of fighting violence associated with specific events. Moreover, section 44 of the Terrorism Act 2000 (s44) allows senior police officers to authorise stop and search without reasonable suspicion if deemed necessary to prevent acts of terrorism, though this has since been repealed.

The use of police powers to stop and search citizens in England and Wales varies considerably across time and place (Bradford, 2017), even within London (Tiratelli et al., 2018). As Shiner & Delsol (2015) suggest, variations in the use of such powers are directly associated with the broader politics of crime control. With the promise of deterring future criminal behaviour, increases in the number of stop and searches – particularly the 'suspicion-less' variety – can be framed within a 'toughening of crime control' political ideology, which is more or less popular depending on the political climate. At the same time, previous research in the UK has identified high levels of ethnic disproportionality in the use of S&S powers (see Bowling & Phillips, 2007; Shiner et al., 2018). This study tackles this double aspect of policing – crime deterrence and social control, or "parking tickets and class repression" (Marenin, 1982) – by assessing **where** police stops and searches are concentrated in the UK capital. What can the spatial heterogeneity of S&S in a city like London tell us about police mechanisms of social control?

5.2.2 S&S as a strategy for crime deterrence?

Police powers to stop and search members of the public are justified using a number of reasons. Notably, police reports often emphasise the importance of S&S to investigate crime and to apprehend weapons (MET, 2014). But one of the main motivations for the persistence of S&S is the promised deterrent effect on crime – the promise that increasing the number of police stops and searches will have a downstream effect on crimes, especially knife crime and drug offences (see May, 2014).

Deterrence theory premises that rational individuals will be deterred from engaging in offensive behaviour should the costs (e.g., punishment) outweigh potential gains from their behaviour [becker1968crime]. Two important mechanisms are often listed as effective crime deterrents: the certainty and the severity of punishment (Apel & Nagin, 2011). In the case of S&S, the former is the theoretical foundation for its effectiveness: by increasing the number of police stops, potential criminals would perceive a higher likelihood of being caught and therefore be deterred from carrying knives or drugs. An important aspect of S&S is to therefore appear risky for potential offenders. Though theoretically sound, a sensible empirical question is: does it actually work? Is S&S effective in deterring crime (Delsol, 2015)?

This was the primary question posed by Tiratelli et al. (2018). Using stop and search data for every borough in London from April 2004 to November 2014, the authors used lagged dependent variable models to estimate the effect of the number of stops and searches in one week or month on a number of crime rates in the following week or month, controlling for previous crime rates. They also relied on interrupted time series models to estimate the effect of the sudden increase in the use of ‘suspicion-less’ stops and searches (based on s60) between 2007 and 2011 on subsequent crime rates. They found very little evidence that S&S has a deterrent effect on crime – there were no effects on robbery and theft, vehicle crime or criminal damage, very small or no effects on burglary, non-domestic violent crime and total crime. Only drug offences appeared to be somewhat affected by variations in S&S, though even in this case the causal mechanism is not clear (Tiratelli et al., 2018, pp. 1224–1225). Overall, the authors conclude that S&S practices have relatively little deterrent effect.

Another London-based study was conducted by McCandless et al. (2016), who investigated the effect of Operation BLUNT 2 on crime rates. Operation BLUNT 2 was a large initiative that involved the increase of suspicion-less stop and searches based on s60 in some boroughs. The authors used difference-in-differences to assess the policy impact on knife crime comparing boroughs where the policy was implemented with boroughs where it was not. In summary, they found that the increase in s60-based stop and searches had no effect on police recorded crime. Other studies corroborate the lack of empirical evidence on the effect of similar policing strategies worldwide on crime rates, most notably in the context of New York City's Stop, Question and Frisk (SQF) policy (Fagan, 2016; MacDonald et al., 2016; Rosenfeld & Fornango, 2014; D. Smith et al., 2012).

Taken together, there is no consensus on the effect of S&S on crime rates. Evidence points to heterogeneous impacts of this type of policy strategy depending on spatial differences and the type of crime (Weisburd et al., 2016), but overall studies find no or little decreases in most crime rates. Given the apparent ineffectiveness of stopping and searching members of the public, another question posed by the literature is around the persistence of S&S practices (Bradford, 2015). Specifically, recent studies have investigated empirically whether interpretation of S&S practices as a tool of social control provides the explanation.

5.2.3 S&S as a tool of social control?

Previous studies find very little evidence that S&S practices have a deterrent effect on crime rates. Why, then, are S&S powers still so commonly used? Tiratelli et al. (2018) argue that, apart from officers' beliefs that this is a useful tool of crime control, S&S practices are not solely about crime – "it is also a tool of order maintenance, used by police officers seeking to assert power and control in a situation or locale" (p. 1226). A large body of previous research on the cultural meaning of policing powers has suggested the interpretation of police as an institution of social ordering that provides identities to the policed depending on their position in structural relationships (see Bradford & Loader, 2016). In that sense, stop and search powers contribute to protect the boundaries of inclusion and exclusion (Peter AJ Waddington, 1999) as police contact contains status-relevant information about citizens (see Oliveira et al., 2020).

The interpretation of S&S powers as a tool of social control is often linked to ethnic disparities, which have been extensively documented by previous research. Black, Asian, and minority ethnic (BAME) groups are more likely to be stopped and searched than their white counterparts – for instance, as of 2017 Black people were stopped and searched more than eight times the rate of white people (Shiner et al., 2018). Even if official statistics alone can be limited in proving police discrimination (see Quinton, 2015), race disproportionality in S&S is certainly an indication of unlawful racial discrimination (Bowling & Phillips, 2007). Ethnic disparities in the police use of S&S powers is a social problem yet to be tackled, and one that has worsened as the overall number of S&S decreased over the last decade (Shiner et al., 2018).

A common explanation for the disproportionate use of S&S powers focuses on contextual circumstances that make some people "available" for being stopped and searched (see Philip AJ Waddington et al., 2004). When compared to the "available population" (as opposed to comparing to the general population), there would be no or very little ethnic disparities ("available" meaning people who use public places when and where stops and searches take place (Miller et al., 2000)). However, a report from the Equality and Human Rights Commission (2010) characterised this study's methodology as 'self-fulfilling' (Bridges, 2015) and counter-argued that "street availability is influenced by police decisions where and when to do stops and searches and these decisions heavily influence the people that are 'available' to be stopped and searched" (EHRC, 2010, p. 57).

This debate raises an important issue. If demonstrating *who* is stopped and searched is one of the ways in which the interpretation of S&S as a tool of social control finds empirical basis, investigating *where* the stops and searches happen might prove to be an important strategy to explain the mechanisms through which S&S powers are exercised. Studying the spatial distribution of S&S can explain how the "available population" are filtered out.

To address this, we analyse stop and search data from London in 2019, aggregated by Lower Super Output Area (LSOA). LSOAs are areas designed for census purposes and to improve local statistics in England and Wales. They are also population-weighted, containing on average 1,691 residents (SD = 263). To introduce the data, Figure 10 shows the spatial distribution of the number of stop and searches by LSOA – it is possible to see a highly heterogeneous distribution, with a higher concentration of stops in the Central, North East, and West parts of the UK capital.[21]

[21] All police forces in the UK make S&S and crime data publicly available: https://data.police.uk/.

Our question is what drives this spatial distribution. If not previous crime rates (i.e., S&S as a strategy for crime deterrence), what spatial features could influence police decisions where to stop and search members of the public? Our hypothesis – based on the interpretation of S&S as a tool of social control – is that economic inequality plays a role, with more unequal locations being more susceptible to S&S practices even when holding previous crime rates constant. According to a model of social control put forward by Choongh (1998), aspects of police behaviour and activity can be seen as seeking to 'subordinate sections of society' which are deemed inherently criminal (p. 623). The poor are one such section, and it is therefore in areas where the poor and rich live side-by-side where police are more likely to be primed to wield S&S as a tool of social control.

To test this hypothesis, we use a novel measure of salient, spatially-granular economic inequality at the LSOA-level based on the estimated value of around 23 million UK residences (Suss, 2021). One of the advantages of our measure is that it is more perceptible to individuals, given that it's based on a major feature of the built environment used by individuals to make distributional assessments (i.e. quality of houses), as opposed to unobservable features (e.g. income of residents) (see Suss, 2021). Suss (2021) finds housing value inequality to be substantively associated with individual perceptions of local economic inequality in the UK across two surveys. This perceptual point is important because we believe that observing the juxtaposition of rich and poor is more likely to trigger the social control motive for S&S. Figure 11 shows the spatial distribution of housing value inequality as measured by the Gini coefficient – a commonly used measure of economic inequality – for London in 2019 at the LSOA-level.

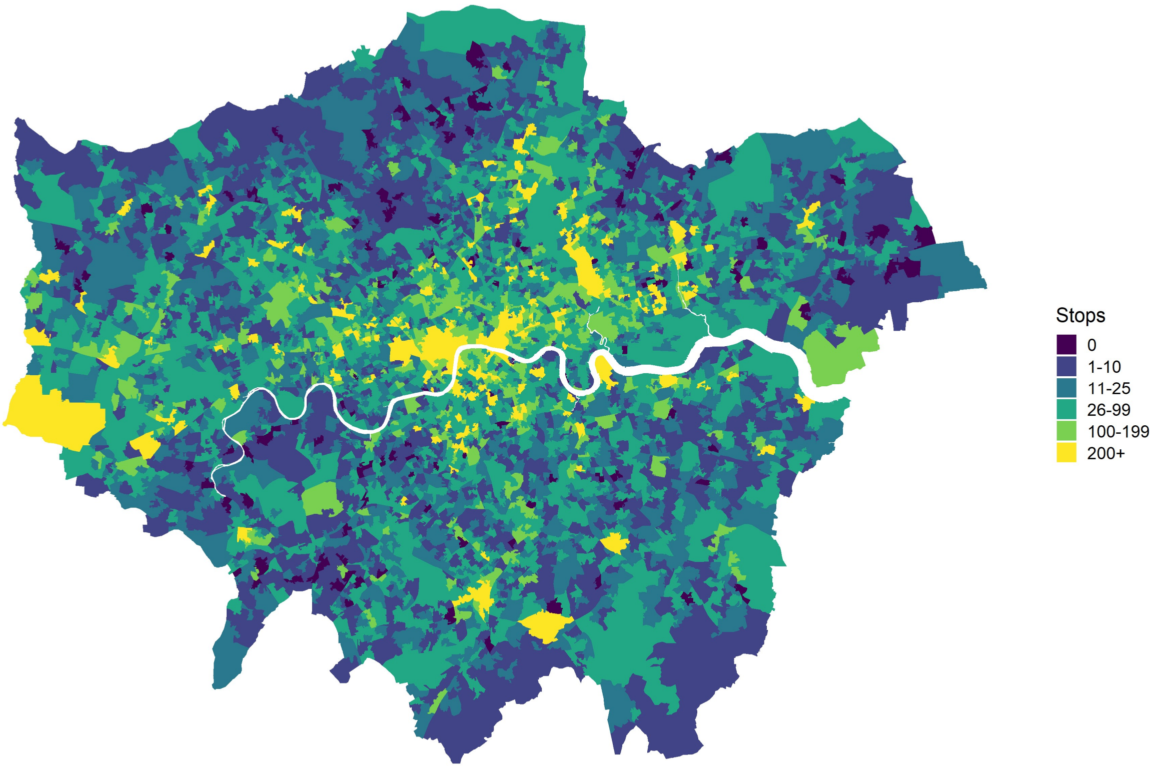
5.3 Data and methods

Our response variable consists of the number of stop and searches in 2019 by LSOA (N = 4,835). The distribution of S&S is highly skewed – 18.1% of locations had no more than 5 stops and searches in 2018, whereas a single LSOA had 2,123 of such police stops. The median number of stops is 20, while the average is 49.8 and the mode is just 5 – which speaks to the highly unequal distribution of S&S powers across Greater London. Figure 10 maps the spatial distribution of stops in London for 2019.

Our main explanatory variable is a measure of economic inequality based on housing values. The data comes from the online property aggregator Zoopla and was gathered in September 2019.

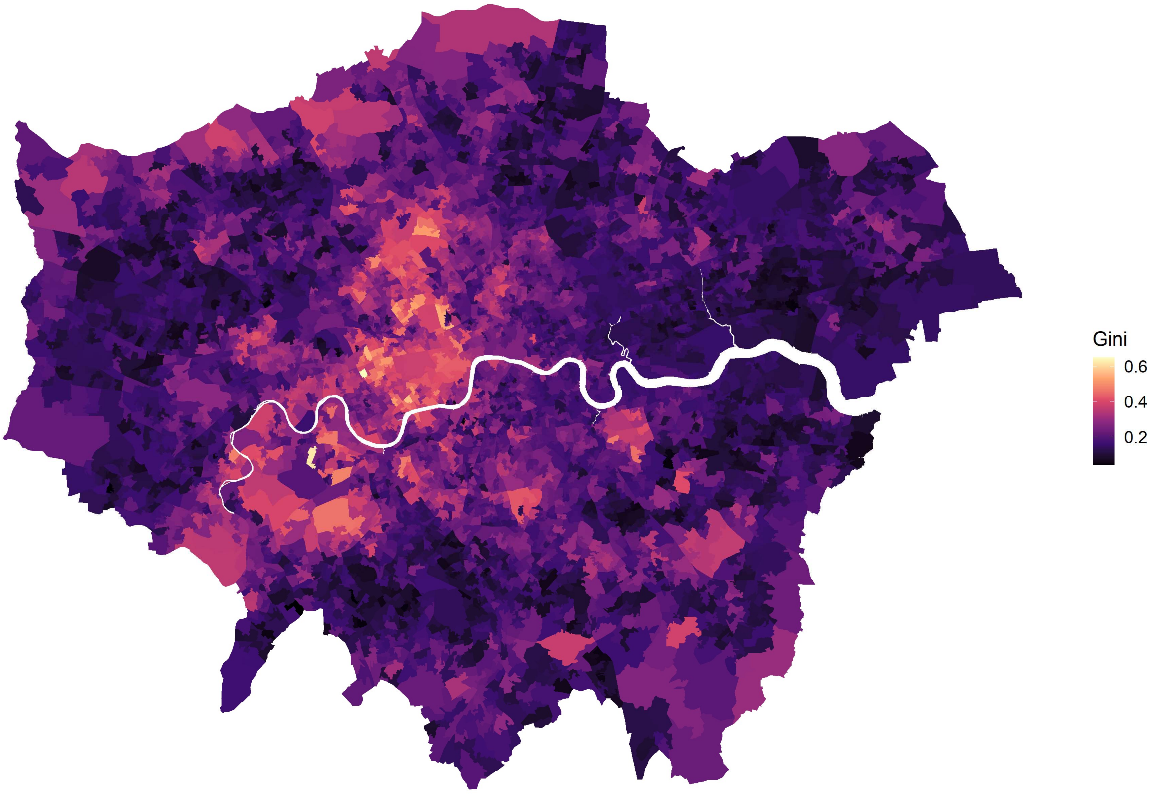
The size of the data (approximately 23 million observations for the UK) allows us to measure economic discrepancies at a far more granular level than possible with conventional data sources (Suss, 2021). We estimate inequality down at the LSOA-level to match the S&S data (average of 516 housing value observations per LSOA). The Gini coefficient ranges from 0.042 to 0.649, with a mean value of 0.198 – see Figure 11 for a map of inequality in London.

Figure 10: Number of Stop and searches – London, 2019, LSOA-level



Note: The figure shows the spatial distribution of police stops and searches for London, 2019. The data was downloaded from https://data.police.uk/.

Figure 11: Housing value inequality – London, 2019, LSOA-level



Note: The figure shows the spatial distribution of within-LSOA housing value inequality for London, 2019. Data on housing values comes from Zoopla and is discussed in Suss (2021). Areas with less than 50 observations are omitted (gray).

5.3.1 Crime as an explanatory variable

As discussed above, one of the stated promises of policing policies, such as the use of S&S powers, is the deterrent effect on crime. Though previous studies have demonstrated the relatively weak deterrent effects of S&S, police forces could potentially allocate their resources – including the decision as to where stop and search members of the public – based on previous crime rates, particularly those related to drug offences (see Tiratelli et al., 2018). If a given location had more drug-related offences registered in the previous year, it is reasonable to assume that police forces would prioritise such location over other, 'less risky' ones. At the same time, local inequality has also been found to be correlated with violence figures (see Kang, 2016). As such, crime rates – particularly previous drug offences – could be confounding the association between local inequality and the number of S&S.

In order to assess the role of crime, we include the following variables in the analysis:

- *Drug Offences in 2018*

We include the rate of drug offences per LSOA for 2018 as control variable (standardised by LSOA workplace population taken from the 2011 census). This is taken from data made publicly available by the UK police (https://data.police.uk/). Temporally lagged drug offences are our most important control variable, given that drugs is one of the primary reasons cited by police for performing S&S and the only type of offence moderately affected by variations in the use of S&S according to previous research (Tiratelli et al., 2018).

- *Multiple Deprivation Indices, Crime domain scores for 2019*

In order to control for the level of crime at the LSOA-level more generally, we include the crime domain scores from the 2019 Index of Multiple Deprivation (IMD; Government (2015)). The score comprises four indicators, based on data from between 2016 and 2018, related to rates of violence, burglary, theft, and criminal damage. This index is another crucial control variable. Theoretically, police forces could decide on resource allocation – including S&S allocation – based on how violent neighbourhoods were in the past, which is also potentially associated with levels of salient inequality. Crime indicators confound the relationship between structural neighbourhood conditions and number of stop and searches.

- *Ethnic composition in 2011*

We include a measure of ethnic composition at the LSOA-level using data from the 2011 census. We construct this as the percent of residents who are non-White. In addition, we include a series of other control variables:

- *Multiple Deprivation Income scores for 2019*

We include the income domain score from the IMD. This comprises indicators for the number of families per area receiving income support, jobseeker's allowance, employment and support allowance, and pension credit. For the detailed description of the domains and methodology, see Government (2015).

- *Average property value (log scale)*

We include the average property value for the area (logged). This, along with the income score, allows us to control for the level of affluence per LSOA.

- *Distance to nearest transport hub*

We introduce a measure of the distance (in meters) from each LSOA centroid and the nearest Transport for London (TfL) station (i.e. including underground, overground and rail services).

- *Density*

Finally, we control for population density (defined as the usual resident plus workplace population divided by hectares) from the 2011 UK census. Table 14 provides descriptive statistics for all variables.

Table 14: Descriptive statistics for control variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Stops	4,835	49.770	106.576	0	8	49	2,123
Gini coefficient	4,835	0.198	0.086	0.042	0.136	0.246	0.649
Average house value (thousands)	4,835	604.579	409.549	183	378	677	5,064
Density (workday population / hectares)	4,835	136.985	117.792	2.200	68.450	174.400	1,432.300
Income deprivation score	4,835	0.136	0.076	0.006	0.075	0.189	0.437
Crime deprivation score	4,835	0.258	0.571	-2.354	-0.117	0.637	2.377
Drugs rate (offenses / workplace population)	4,831	0.258	0.303	0.000	0.062	0.338	3.180
Distance to nearest TfL station (meters)	4,835	404.474	445.071	0	72.0	585.4	4,927
Non-white percentage	4,835	39.387	20.367	1.841	22.611	54.204	96.592

5.3.2 Analytic strategy

Theoretically, our hypothesis is that local economic inequality is one of the mechanisms that filter out the "available population" for S&S. But in order to properly assess this hypothesis, we need to take into account potential spatial dependency as well as other confounders (e.g. crime rates). It could be that LSOAs which are close to each other are similar in a number of observed and unobserved features, with police behaviour and structural conditions being just two of those features. The tests we perform in this paper aim to rule out alternative explanations for the spatial association between the number of S&S and salient inequality at LSOA-level.

Our analytic approach is two-pronged. Our goal is to investigate whether there is a spatial association between the number of S&S and the level of economic inequality at the LSOA-level. First, we assess the extent to which the relationship between the two variables remain significant when controlling for spatial effects alongside all control variables described above. To do so, we compare an OLS model that treats stops as a continuous variable with a Spatial Durbin Model

(SDM).[22] The SDM includes spatial lags – taken as the average of all adjoining LSOAs (i.e. the Queen configuration) – for the outcome and regressor variables. This accounts for possible dependence between, for example, stops and searches in any given area with the level of inequality and drugs crime rate in neighbouring LSOAs. More formally:

$$y_j = \rho W y_j + \beta X_j + \lambda W X_j + \epsilon_j$$

where y_j is the number of stops for area j, W is the row-standardised spatial weight matrix (non-zero elements indicate a neighbouring LSOA), X_j is a vector of covariate values with associated β parameters to be estimated, ρ and λ are the parameters for the dependent and independent spatial lags, and ϵ_j is the error term.

Second, we employ negative binomial regression models to evaluate the relationship between police stops and inequality. Given that the number of S&S by LSOA is a count variable whose standard deviation exceeds the average (i.e. overdispersion), this model specification is well suited. However, we are unable to account for spatial effects using this model given the limitations that result from including the spatial lag in the exponential function (Glaser, 2017). The negative binomial model takes the form:

$$ln(\mu_j) = \beta_0 + \beta X_j + \epsilon_j$$

where μ_j is the expected value of our outcome measure for area i with variance $\mu + \mu^2/\theta$, β_0 is the intercept, X_j a vector of independent variables, and β a vector of coefficients to be estimated (along with θ) using maximum likelihood.

5.4 Results

First, we compare the OLS coefficient estimates with that of the SDM. The Moran's I test statistic on the OLS residuals reveals spatial correlation (p < 0.01), but this is no longer the case when introducing the spatial lags – a Monte-Carlo simulation of Moran's I reveals the SDM model residuals are not spatially correlated (p = 0.746; based on 1000 simulations).

[22] The SDM aligns with our theoretical expectations for the process that might create spatial dependence between the regressors and police stops, however we also explore the fit of other spatial regression models and whether these affect our coefficient estimate for inequality (unreported). They do not.

Table 15 displays the output from the OLS and Durbin models. Both models control for the average property value (log scale), income and crime deprivation scores, population density (log scale), the percent of non-White residents, distance to the nearest TfL station, and the 2018 rate of drug crimes. The coefficients for the spatial lags of the drug crime rate and TfL station distance are found to be significant ($p < 0.01$; not shown), as is ρ, the coefficient on the lag of the dependent variable ($p < 0.01$). Taking into account the spatial autocorrelation of neighboring LSOAs, we can see that the greater the level of economic inequality of a location, the higher the number of stops and searches – this is the case in both the OLS and the SDM models, with the size of the coefficient becoming slightly smaller in magnitude once spatial effects are taken into account. Specifically, considering Column 2 of Table 15, a standard deviation increase in the Gini coefficient (SD = 0.086) is associated with more than 6 additional police stops.

Table 15: OLS and SDM regression results

	Dependent variable:	
	Stop and searches, London (2019)	
	OLS	*Spatial autoregressive*
	(1)	(2)
Gini	7.239***	6.135***
	(2.051)	(1.903)
Avg value (log)	-7.642***	-6.393**
	(2.367)	(2.544)
Density (log)	15.275***	8.041***
	(1.555)	(2.240)
Income deprivation	-12.942***	-10.709***
	(2.036)	(2.015)
Crime deprivation	11.168***	8.390***
	(1.663)	(1.718)
Drugs rate	43.682***	41.770***
	(1.561)	(1.583)
Non-white (%)	0.956	8.389**
	(1.713)	(3.734)
TfL station distance	-4.547***	-15.158***
	(1.428)	(2.970)
Rho		0.42
Observations	4,831	4,831
R^2	0.246	
Adjusted R^2	0.244	
Log Likelihood		-28,456.730
sigma^2		7,396.195
Akaike Inf. Crit.		56,951.450
Residual Std. Error	92.673 (df = 4822)	
F Statistic	196.252*** (df = 8; 4822)	
Wald Test		589.226*** (df = 1)
LR Test		504.319*** (df = 1)
Note:	*p<0.1; **p<0.05; ***p<0.01	
	All independent variables are standardised (mean equal to zero, standard deviation equal to one).	

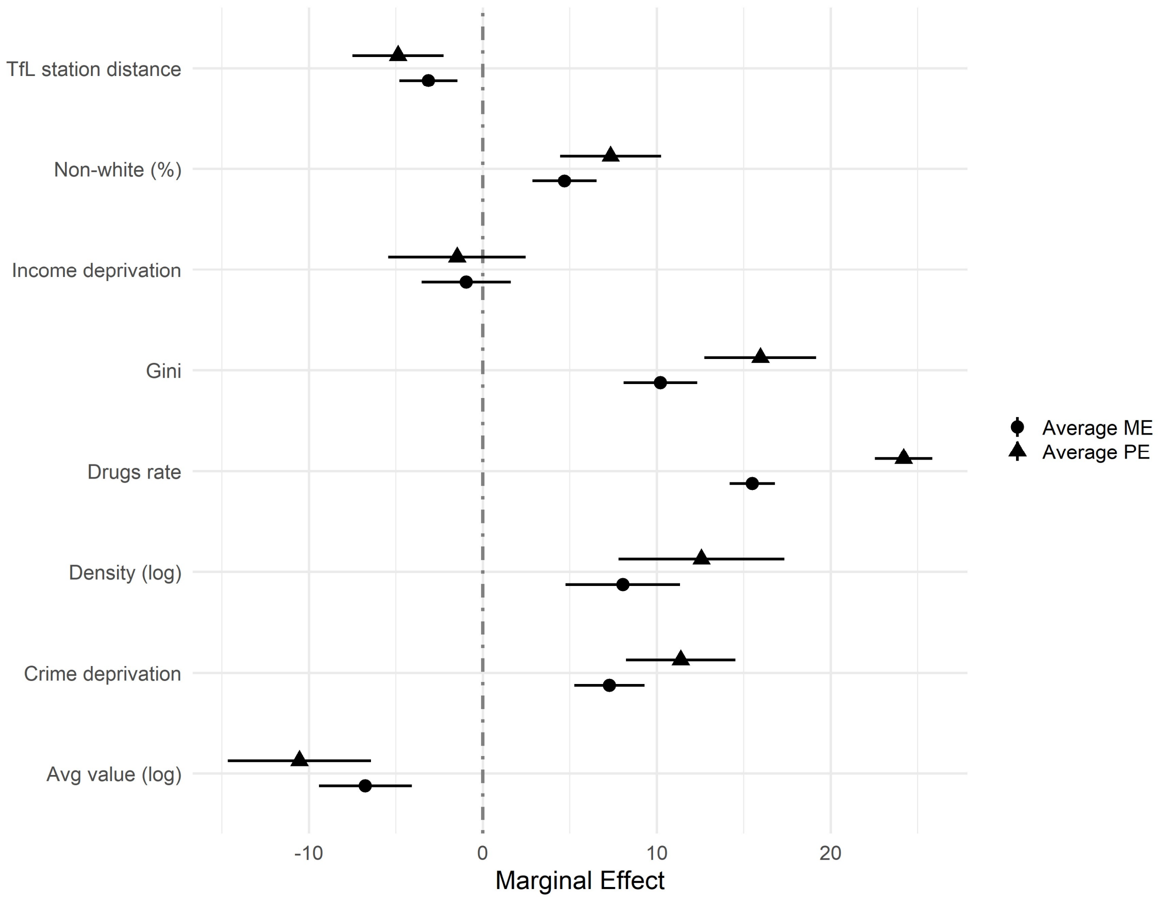
Next, we present the results for the negative binomial regression models in Table 16. Column 1 just contains the inequality variable and Column 2 adds all the control variables. The results indicate that the coefficient on our measure of inequality is significant and slightly larger when introducing the controls. We can get a sense of the substantiveness of this effect by taking the exponent of the coefficient, known as the Incidence Rate Ratio (IRR). For Column 2, the IRR is 1.34, which indicates that the expected number of stops is expected to increase by 34% for a one standard deviation increase in inequality, controlling for all other variables in the model. This is a large figure. To put it into perspective, the IRR for the rate of drug offences in 2017 is 1.56 and the crime deprivation score 1.23, so the expected percent increase in S&S stemming from inequality is over half of the effect of temporally lagged drug offences and 11 percentage points larger than the effect of the crime score.

For a more complete picture of the substantiveness of the results, we calculate the marginal effects for Column 2 in Figure 12. We do so in two ways: first, the marginal effect when each covariate is at its average value, and second the average partial effect over every observation. From the first approach, we find that a one standard deviation increase in the level of inequality is expected to increase the number of stops by between (roughly) 7 and 13. The equivalent range for the average partial effect is approximately 12 and 18.

Table 16: Negative binomial regression results

	Dependent variable:		
	Stop and searches, London (2019)		
	(1)	(2)	(3)
Gini	0.178***	0.292***	0.271***
	(0.018)	(0.023)	(0.023)
Avg value (log)		-0.193***	-0.213***
		(0.026)	(0.027)
Density (log)		0.230***	0.232***
		(0.017)	(0.017)
Income deprivation		-0.027	-0.043*
		(0.023)	(0.023)
Crime deprivation		0.208***	0.204***
		(0.019)	(0.019)
Drugs rate		0.442***	0.444***
		(0.017)	(0.017)
Non-white (%)		0.134***	0.131***
		(0.019)	(0.019)
TfL station distance		-0.089***	-0.092***
		(0.016)	(0.016)
Gini : Income deprivation			-0.081***
			(0.017)
Observations	4,831	4,831	4,831
Log Likelihood	-23,344.670	-22,102.930	-22,091.630
theta	0.636*** (0.012)	0.974*** (0.019)	0.978*** (0.019)
Akaike Inf. Crit.	46,693.340	44,223.860	44,203.250
Note:	*p<0.1; **p<0.05; ***p<0.01		
	All independent variables are standardised (mean equal to zero, standard deviation equal to one).		

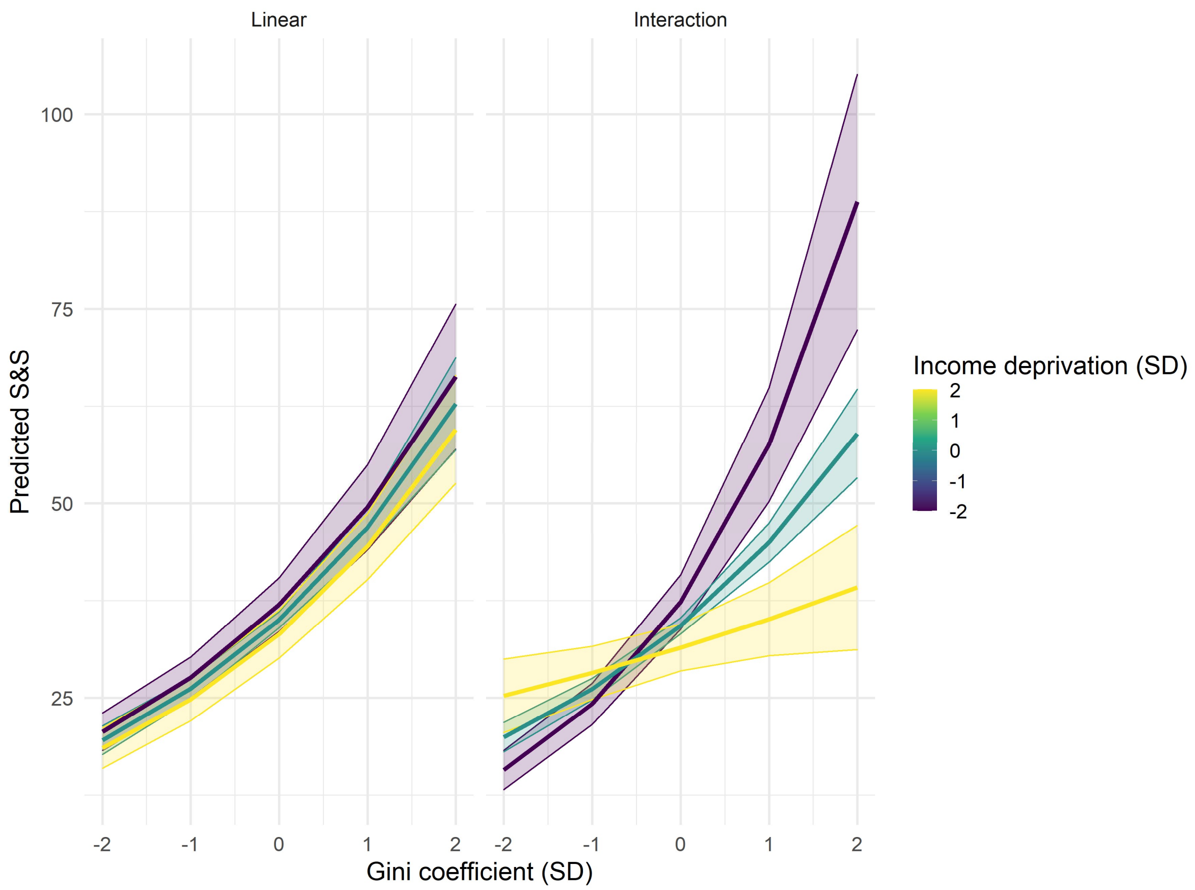
Figure 12: Marginal and average partial effect of inequality and other covariates on S&S



Note: The figure shows the marginal effect and average partial effect for each covariate for Column 2 of Table 16 with 95% confidence intervals.

Column 3 in Table 16 introduces an interaction term between inequality and the income deprivation score, which we find is negative and significant. This indicates that the effect of inequality on S&S depends on the local level of affluence, with the magnitude of the effect larger as affluence increases. This is a striking finding. It means that while there appears to be an effect of economic inequality on the number of police stops and searches, this effect is not homogeneous across LSOAs. When a given location is characterised by high levels of income deprivation (i.e. is relatively poorer), the relationship between economic inequality and police behaviour is weaker; when a location is relatively affluent, the expected effect of economic inequality on the number of S&S is much higher. Figure 13 plots the predicted number of stops for Column 2 as compared to Column 3 with the interaction term included and helps visualise the interaction effect. The figure demonstrates that relatively affluent areas (defined as being two standard deviations below the mean income deprivation score), are expected to see approximately 5 times fewer police stops when inequality is low versus high (defined as two standard deviations below versus above the mean Gini value).

Figure 13: Effect of interaction term on predicted S&S



Note: The figure shows the how the predicted stops is affected by introducing a interaction term between inequality and income deprivation (Column 3 of Table 16). We fix all other covariates at their mean values. Shaded areas are 95% confidence intervals.

Finally, we check whether our results are London-specific or whether the relationship between economic inequality and S&S generalises to other urban contexts. To evaluate this, we re-run the negative binomial specifications for other major cities in England: Birmingham, Liverpool and Manchester. Results can be found in Table A.19 of the Annex, but it suffices to say that they remain virtually unaltered – local economic inequality is associated with a higher number of police stops and searches in these cities as well.

5.5 Discussion and conclusion

Criminologists have long studied the purpose and potential effects of police powers to stop and search members of the public. Either based on reasonable suspicion or completely "suspicion-less" (such as those based on s60 in the UK), increases in the use of S&S powers are often followed by intense public discussions about the usefulness of such policies. Policymakers usually defend S&S practices praising its effective deterrent effects, especially on drug offences and knife crimes. However, previous work both in the UK and elsewhere has demonstrated that stopping and searching members of the public has at best a marginal effect on preventing future offending behaviour (MacDonald et al., 2016; McCandless et al., 2016). In London specifically, only drug offences appear to be affected by an increase in S&S practices, and only to a small extent (Tiratelli et al., 2018). Given this context, we ask: what justifies the persistence of this policing strategy?

Previous research over decades has suggested that S&S is not solely about crime-fighting, it is also about social order maintenance – i.e. it is a tool used by officers to assert power and control (Choongh, 1998; Tiratelli et al., 2018). In this we paper we extend this argument by looking at the spatial distribution of searches in the city of London in 2019. Keeping previous crime rates and drug offences constant, we demonstrate that police officers tend to engage in more searches in more economically unequal locations – i.e. the decision regarding *where* to stop and search members of the public consists of yet another way for police to ascribe identity to the populations they police (Bradford & Loader, 2016, p. 1226).

Focusing on the spatial distribution of S&S in London allowed us to assess the extent to which the number of searches by location is associated with various other spatially-relevant variables. We used data at LS0A-level and drew on a novel measure of salient, spatially-granular economic inequality as developed by Suss (2021). This data provides estimated housing values for around 23 million addresses in the UK, allowing us to investigate the effects of local inequality at a level not before possible. Furthermore, using housing values rather than income figures is theoretically sound as it has been shown to substantively affect people's perceptions of economic discrepancies (Suss, 2021). This unique measure of economic inequality allows us to investigate the mechanisms of police decision-making regarding S&S in a way that was not possible before.

Additionally, investigating the spatial concentration of S&S also allowed us to provide an alternative explanation for the "available population" argument. Even if the high levels of ethnic disparities in S&S in the UK (Shiner et al., 2018) emerge as a consequence of the people who are on the streets when stops and searches happen, police officers still decide when and where to use their S&S powers. As our study shows, LSOAs characterised by higher levels of economic inequality are prioritised over other locations, which suggests – as expected – that police decisions are themselves responsible for filtering out the available population.

We approached this issue using two complementary analytical strategies. First, we used Spatial Durbin models to analyse the spatial association between economic inequality and the number of S&S by LSOA whilst taking into account the number of S&S and other covariates in neighbouring LSOAs. This model was important as it allowed us to assess the extent to which there was an association between the two variables even when spatial effects were considered. The SDM showed that highly unequal locations saw higher volumes of searches, whereas more economically homogeneous locations do not see as many. Second, we investigated this further by using negative binomial regression models, given that the number of S&S by LSOA is a count variable. These regression models confirmed our results, showing that increases in the Gini coefficient are associated with significant and substantive increases in the number of searches by LSOA.

Furthermore, we found a significant and negative interaction between economic inequality and income deprivation. This means that, whilst there is an association between inequality and the number of searches, the effect is not homogeneous. The more affluent an LSOA is – i.e. low levels of income deprivation – the stronger the effect of inequality on S&S. This is a striking result. The fact that income deprivation alone does not influence the spatial concentration of searches but economic inequality does suggests that local wealth alone is not a factor taken into account when officers decide to employ their S&S powers. Instead, the factor is the distribution of wealth. Whilst a homogeneously wealthy or poor neighbourhood will not stage as many searches, a heterogeneous location where the gap between wealthy and poor residents is large will have plenty. Among those heterogeneous locations, the wealthier the neighbourhood is, yet the more searches will occur. These results suggest that S&S powers are indeed employed as a tool of social control, protecting and asserting power of some segments of society over others.

Limitations should, of course, be acknowledged. First, we are not claiming causality. There could be omitted variable bias confounding the relationship between economic inequality and the number of searches by LSOA, given that we – obviously – did not randomly assign levels of inequality, nor did we engage in any particular identification strategy. Future research should employ quasi-experimental designs to potentially assess the causal effect of the association we found. Second, we only analysed data from London and other English cities. Other contexts, such as the Stop, Question, and Frisk policies in the US could have different spatial properties relative to those in the UK. Third, we did not distinguish between searches based on reasonable suspicion and 'suspicion-less' searches based on s60 – it is possible that they have different spatial distributions. We would welcome studies focusing on more nuanced analysis of S&S in the UK and elsewhere. Finally, we only analysed data from 2019 – future research could model time series assessing the extent to which structural neighbourhood conditions continuously influence the use of S&S powers.

Despite these limitations, the results presented in this paper provide new and valuable evidence on the relationship between economic inequality and policing behaviour, and on S&S policies as a form of social control.

5.6 Annex

Table 17: Stop and searches: Birmingham, Liverpool, and Manchester (2019)

	Birmingham		Liverpool		Manchester	
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.232***	0.230***	0.155***	0.155***	0.239***	0.218***
	(0.028)	(0.028)	(0.037)	(0.037)	(0.043)	(0.044)
Avg value (log)	-0.127***	-0.143***	-0.135*	-0.140**	0.019	0.017
	(0.046)	(0.048)	(0.070)	(0.071)	(0.061)	(0.064)
Density (log)	0.209***	0.211***	0.030	0.030	0.390***	0.292***
	(0.031)	(0.031)	(0.036)	(0.036)	(0.049)	(0.051)
Income deprivation	-0.058	-0.074	0.180***	0.173***	-0.054	-0.031
	(0.045)	(0.047)	(0.058)	(0.062)	(0.064)	(0.067)
Crime deprivation	0.295***	0.297***	0.422***	0.422***	0.374***	0.368***
	(0.033)	(0.033)	(0.048)	(0.048)	(0.054)	(0.055)
Drugs rate	0.329***	0.328***	0.395***	0.395***	0.314***	0.304***
	(0.027)	(0.027)	(0.036)	(0.036)	(0.041)	(0.041)
Non-white (%)	0.339***	0.342***	0.183***	0.184***	0.171***	0.196***
	(0.030)	(0.031)	(0.032)	(0.032)	(0.043)	(0.044)
Rail station distance	-0.307***	-0.306***	-0.171***	-0.172***	-0.147***	-0.123***
	(0.027)	(0.027)	(0.031)	(0.032)	(0.041)	(0.042)
Gini : Income deprivation		-0.030		-0.014		-0.005
		(0.027)		(0.035)		(0.041)
Observations	1,680	1,680	910	910	1,673	1,673
Log Likelihood	-5,330.284	-5,329.669	-3,443.683	-3,443.595	-2,755.058	-2,760.043
theta	1.201*** (0.049)	1.202*** (0.049)	1.352*** (0.068)	1.353*** (0.068)	0.580*** (0.034)	0.583*** (0.035)
Akaike Inf. Crit.	10,678.570	10,679.340	6,905.365	6,907.190	5,528.115	5,540.086
Note:	*p<0.1; **p<0.05; ***p<0.01					
	All independent variables are standardised (mean equal to zero, standard deviation equal to one).					

6 Diversity, segregation, and support for Brexit

Abstract: *What effect does local economic inequality and ethnic diversity have on voting behaviour? This question is of increasing importance as many cities in the US, UK and other developed countries experience rising inequality and immigration. Using Brexit as a case study, and exploiting unique, hyper-localised data on economic inequality and migration, I explore the impact of neighbourhood composition on voting behaviour. I find evidence that both economic and ethnic diversity are associated with reduced support for Brexit. However, this effect is mitigated by segregation – neighborhoods that are more highly segregated tend to show greater support for Brexit.*

6.1 Introduction

The UK's decision to leave the EU – to 'Brexit' – in a referendum on 23rd June 2016 is widely considered a by-product of increasing economic and cultural divides. The economic narrative in the emerging academic literature is that Brexit was driven by the people and places 'left behind' (Colantone & Stanig, 2018; Goodwin & Milazzo, 2017; Hobolt, 2016; Rodríguez-Pose, 2018). More specifically, those on the losing end of globalisation, i.e. with less education and residing in declining areas, were more likely to support Brexit. To make matters worse, austerity beginning in 2010, which disproportionately affected the people and places most affected by globalisation, 'activated' support for anti-EU politics (Fetzer, 2019).

A second, compatible explanation focuses on the growth in cultural divisions. According to this account, long-term cultural changes in the UK (as well as the US and other Western societies), deriving in particular from increased immigration and ethnic diversity, resulted in countervailing conservative and nationalist reactions. In the UK, this has manifested itself as anti-immigrant and 'Eurosceptic' attitudes, leading to the emergence of right-wing populist political parties (Carreras et al., 2019; Curtice, 2016; Kaufmann, 2016; McLaren, 2002; Norris & Inglehart, 2019) and the desire to 'take back control.'

However, a close examination of the data reveals that there is more to the Brexit story. For one, as Danny Dorling (2016) points out, when accounting for differential population size, it becomes apparent that most Leave voters were middle class and from the relatively affluent, populous

South of England, a world removed in compositional and contextual terms from the struggling post-industrial areas in Wales and the North of England most affected by globalisation and austerity. In other words, it is not only the places 'left behind' but also many that have done relatively well that voted for Brexit. For example, Upminster in East London voted 63% in favour of Leave with an £81,300 average yearly income in 2016.[23] Conversely, many areas which might reasonably considered to be 'left behind,' for example Tottenham Hale in North East London voted overwhelmingly to Remain (84.5%).[24]

Second, there are some notable inconsistencies in the cultural narrative as well. In particular, studies generally show, with some exceptions (Goodwin & Milazzo, 2017), that higher levels or changes in immigrant populations are related to *less* support for Brexit (Arnorsson & Zoega, 2016; Becker et al., 2017; Colantone & Stanig, 2018). This is counterintuitive – we would expect anti-immigrant backlash to be higher in areas which have experienced more immigration.

In this paper, I delve further into the geography of Brexit to address these inconsistencies. In particular, investigate the local contextual drivers of the vote to leave the EU, and shed light on the counterintuitive findings in relation to left behind and anti-immigrant backlash explanations put forward in the literature. In particular, I examine whether important contextual attributes hitherto unexamined – local diversity and segregation – relate to support for Brexit. Diversity refers to compositional variety within a local area (i.e. the variety of different types of economic and social groups), whereas segregation measures its spatial arrangement. To understand what is driving differential voting and support patterns with regards Brexit, I examine the effects of diversity and segregation for two different attributes – economic and ethnic.

Why would diversity matter? Academics differ on the answer to this question – diversity is thought to either increase inter-group conflict ('conflict theory') (Blalock, 1967) or reduce it ('contact theory') (Allport et al., 1954). On the one hand, proponents of conflict theory argue that ethnic diversity increases the opportunity for inter-group strife. This is a central plank in the

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[23] Average income figure from ONS small-area (MSOA) estimates for 2016 merged into 2016 electoral wards. Data is available publicly here: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesformiddlelayersuperoutputareasenglandandwales.

[24] Data on voting obtained from UK Electoral Commission, available publicly here: https://www.electoralcommission.org.uk/who-we-are-and-what-we-do/elections-and-referendums/past-elections-and-referendums/eu-referendum/results-and-turnout-eu-referendum.

cultural narrative around Brexit. From an economic perspective, diverse neighbourhoods are, by definition, economically unequal, and this therefore might make inequalities salient (H. J. Smith et al., 2012) and heighten class conflict (Newman et al., 2015), reducing support for the 'establishment.' On the other hand, contact theory suggests that diversity reduces the distance between different ethnic and economic groups, fostering social networks and mitigating stigmatisation (Allport et al., 1954; Danny Dorling, 2017). Taken together, local diversity might affect support for Brexit by heightening economic and cultural tensions (the 'conflict' hypothesis) or by fostering greater cross-group understanding, thereby mitigating the economic and cultural rationales considered to be drivers of Brexit support (the 'contact' hypothesis).

The empirical evidence relating neighbourhood ethnic and foreign composition and political outcomes is mixed. While some find a positive effect between diversity and populist sentiment (Harmon, 2018; Newman et al., 2018; Putnam, 2007; Reny & Newman, 2018), other find no impact (Hill et al., 2019), or that increased diversity reduces populist support and promotes social cohesion (Kaufmann, 2017; Sturgis et al., 2014). Regarding Brexit in particular, one study surveyed 400 UK citizens just prior to the referendum in 2016, finding that inter-group contact was associated with support for Brexit, although the direction depended on whether the contact was subjectively rated as positive or negative (Meleady et al., 2017). Recent work looking at residential context and far-right voting in France suggests that the chosen geographic scale is important, with positive (negative) effects found for the neighbourhood (department) level (Vasilopoulos et al., 2021). This provides motivation to explore the role of ethnic diversity and segregation on support for Brexit, and to explicitly vary the geographic unit of analysis.

In terms of economic diversity, the empirical evidence is limited. In the US, Newman et al. (2015) finds local inequality increases class awareness and conflict, while in the UK and other European countries there is mixed evidence for the policy of mixed housing conferring benefits (Arthurson, 2002; Bolt et al., 2010; Cheshire, 2007; G. Galster, 2007; Meen & Gibb, 2005; Ostendorf et al., 2001). Granular information on economic heterogeneity in the UK is limited (Suss, 2021), which might explain why there is a lack of studies which examine local economic diversity and its impacts.

Importantly, if there is a positive 'contact' effect arising from diversity, it can be undermined by segregation within neighbourhoods, since a more segregated community does not enable the potentially beneficial contact and interaction to occur (Sturgis et al., 2014) and can make it more difficult to escape poverty (Kearns & Parkinson, 2001; see, for example, Massey & Denton, 1989). So, when evaluating how diversity affects support for Brexit, it is important to also account for the degree of segregation within communities.

The analysis in this paper makes use of fine-grained measures of local economic diversity and segregation based on a large dataset of housing values (Suss, 2021), as well as measures of immigration and ethnicity from the 2011 Census. I merge these data with information on the actual Leave vote from the UK Electoral Commission, as well as individuals' stated levels of support for Brexit in Wave 8 of Understanding Society, a large UK household survey.

By way of preview of the results, I find robust evidence to support contact theory, particularly for ethnic diversity. First, using aggregate-level data on the Leave vote, I present between-area regressions and control for a battery of other known determinants of the Leave vote, demonstrating substantive associations for within-area diversity and segregation on the share of Brexit voters. This holds for both economic and ethnic variables, and the estimates are substantive in size – a one standard deviation increase in economic (ethnic) diversity at the Ward level is associated with a 0.81 (5.61) percentage point reduction in the Leave vote. On the other hand, economic (ethnic) segregation is associated with a 0.85 (1.6) percentage point increase in the Leave vote. The same pattern of results, albeit with slightly reduced point estimates, is found at the Local Authority level.

Second, using individual-level data on support for Brexit, I find that greater ethnic diversity within neighbourhoods leads to substantially higher odds of supporting Remain, and this holds even at more aggregated geographic levels. Segregation has the opposite effect, with more highly segregated neighbourhoods leading individuals to be more supportive of Brexit. Regarding economic diversity and segregation, I find weaker evidence at the individual-level. I also investigate to what extent these contextual effects interact with political orientation, proxied by political party support. The results here are striking and shed light on why Brexit opened up cleavages within established political parties. The segregation effect appears to be operating through supporters of the Labour Party, whereas the diversity effect is broad-based.

While I control for important individual level determinants of pro-Brexit sentiment, and the results are robust to a number of alternative specifications and sub-sample analyses, concerns around endogeneity nevertheless persist, particularly around self-selection – i.e. the possibility that Brexit supporting individuals are more likely to relocate to areas which are less economically and socially diverse. I mitigate this concern by restricting the sample to only those that lived in the same address for 20+ years and to those that live within a 5 mile radius of where they grew up.

This paper proceeds as follows: 6.2 details the data sources and measures; 6.3 describes the methods; 6.4 provides the results and discussion; and 6.5 concludes.

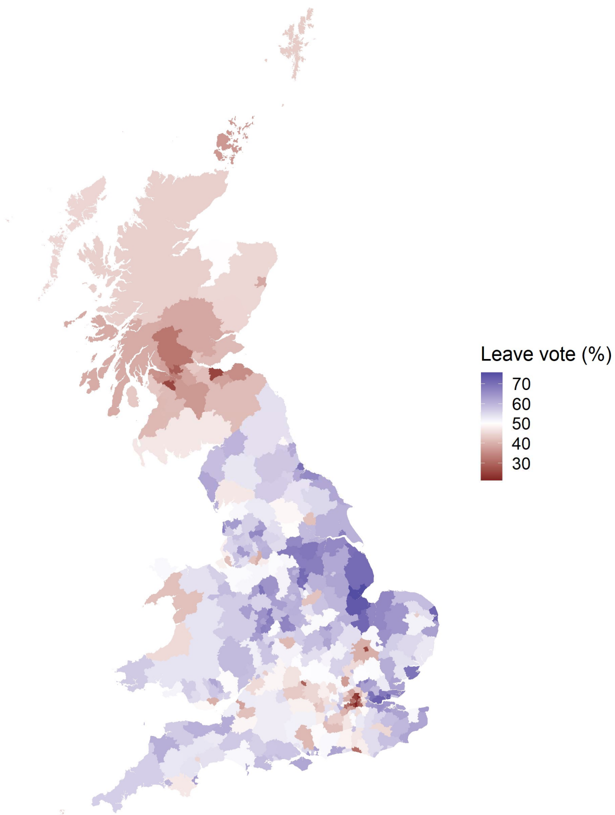
6.2 Data and Measures

6.2.1 Brexit

I obtain data on the actual Leave vote from the UK Electoral Commission.[25] Figure 14 provides the breakdown of the vote for Great Britain (Northern Ireland is excluded because vote tallies are not provided at lower geographical levels).

[25] Data available publicly from: https://www.electoralcommission.org.uk/who-we-are-and-what-we-do/elections-and-referendums/past-elections-and-referendums/eu-referendum/results-and-turnout-eu-referendum.

Figure 14: Proportion Leave by LAD



6.2.2 Diversity and Segregation

For measures of economic diversity and segregation, I use a novel source of highly-granular data on housing values constructed by Suss (2021). This dataset is based on information for approximately 23 million residential addresses from the online property aggregator Zoopla, allowing for statistically reliable measures to be computed at spatially granular levels, down to the Output Area level (the lowest level census geography in the UK). Moreover, Suss (2021) shows that measures of inequality derived from this data are robustly associated with people's subjective perceptions of local economic discrepancies.

For immigration and ethnicity, I use census data from 2011 provided by the ONS. For immigration composition, I take data on country of birth, broken down into the following four categories: UK and Ireland, other EU (not including post-2005 accession countries), EU accession countries (post-2005), and outside UK and EU. For ethnic groups, I select the broad census categories: White, Black, Asian, Mixed, and Other (ONS, 2016).

To measure diversity, I use the reverse of the Herfindahl-Hirschman Index (HHI) concentration index, as follows:

$$HHI = 1 - \sum_{i=1}^{n} s_i^2$$

where s_i is the share of economic or social group i out of the total number of groups in the area n. Higher numbers represent areas that are more diverse. For economic diversity, I discretise the housing value data, rounding all values to the nearest 250k. This results in the possibility of a different number of groups for each area, and so I normalise the score (so that it ranges from 0 to 1). The HHI is often used in studies exploring both economic and ethnic diversity. For example, Minkoff & Lyons (2019) use this measure when examining whether income diversity is related to perceptions of inequality, and Sturgis et al. (2014) when looking at neighbourhood ethnic composition in London.

For segregation, I use the Multigroup Entropy Index (MEI) (Reardon & Firebaugh, 2002; Sturgis et al., 2014; Theil, 1972). This compares the composition of sub-units within an area to surmise the extent of unevenness. The formula is:

$$MEI = \sum_{j=i}^{m} \frac{t_j}{T} \frac{E - e_j}{E}$$

Where T is the population count for the target area and t_j for its sub-units, E and e_j is the entropy score for the larger area and sub-units respectively, calculated as (for e_j):

$$e_j = \sum_{i=1}^{n} s_{ij} \, ln(\frac{1}{s_{ij}})$$

where s_{ij} is the share of economic or social group i out of the total number of groups n in the sub-unit j. The calculation for E is therefore simply $E = \sum_{i=1}^{n} s_i \, ln(\frac{1}{s_i})$. The MEI ranges from 0 to 1, with higher numbers representing greater segregation.

6.2.3 Neighbourhood Definition

I take the Middle Super Output Area (MSOA) as neighbourhood boundaries (population M = 7787.24, SD = 1599.63). MSOAs have a number of properties which are advantageous for approximating neighbourhoods. First, perfectly nested within them are lower level geographies, namely Lower Level Super Output Areas (LSOAs) and Output Areas (OAs), which are in turn built up from postcode blocks. This enables me to easily calculate the MEI by taking the sub-units to be OAs. Second, MSOAs are population-weighted and stable over time. In contrast, other local boundaries, for example electoral Wards, tend to shift boundaries frequently and vary far more in terms of population, and so therefore are not comparable across the UK. I nevertheless measure diversity and segregation at the Ward and LAD levels as well since these are the administrative areas at which the actual referendum vote was counted. I can therefore conduct between-area regressions to examine how the Leave votes relates to the measures of diversity and segregation, whereas for individual-level results I'm confined to self-reported support for Brexit rather than actual voting behaviour.

To provide some indication of the spatial distribution of diversity and segregation, I map out the various measures for select cities in England: Birmingham, Bradford and London. Each of these areas were polarised in terms of Brexit: some Wards saw some areas strongly supporting Leave while others strongly supported Remain. A pairwise correlation analysis (Figure 15) reveals that the ethnic measures are highly correlated with their immigrant counterparts, so I drop the latter going forward in favour of diversity and segregation for country of origin given that the topic was more salient in the Brexit referendum (however I refer to country of origin and ethnic interchangeably).

Figure 16: Ward-level Leave vote, diversity, and segregation (Birmingham)

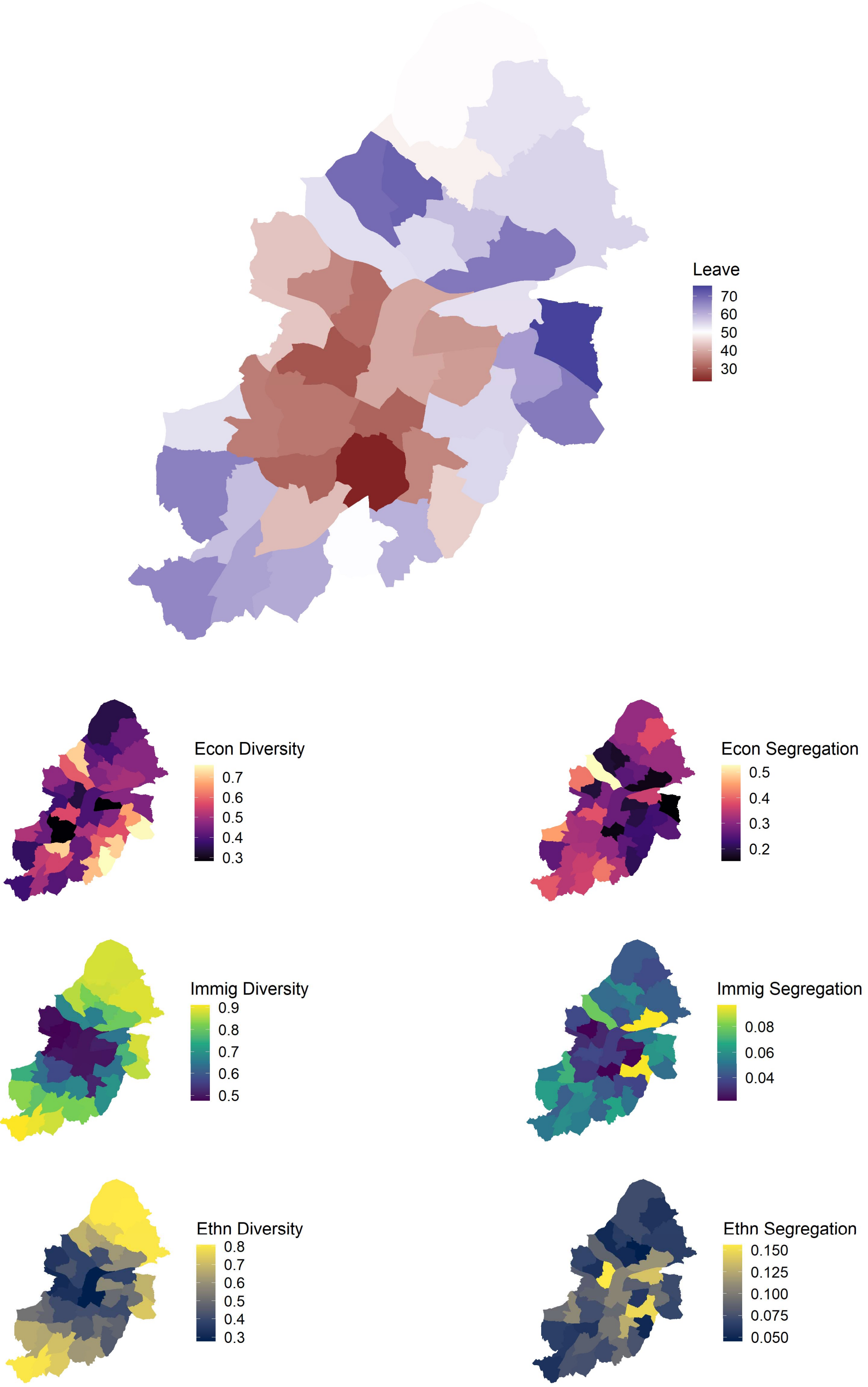


Figure 17: Ward-level Leave vote, diversity, and segregation (Bradford)

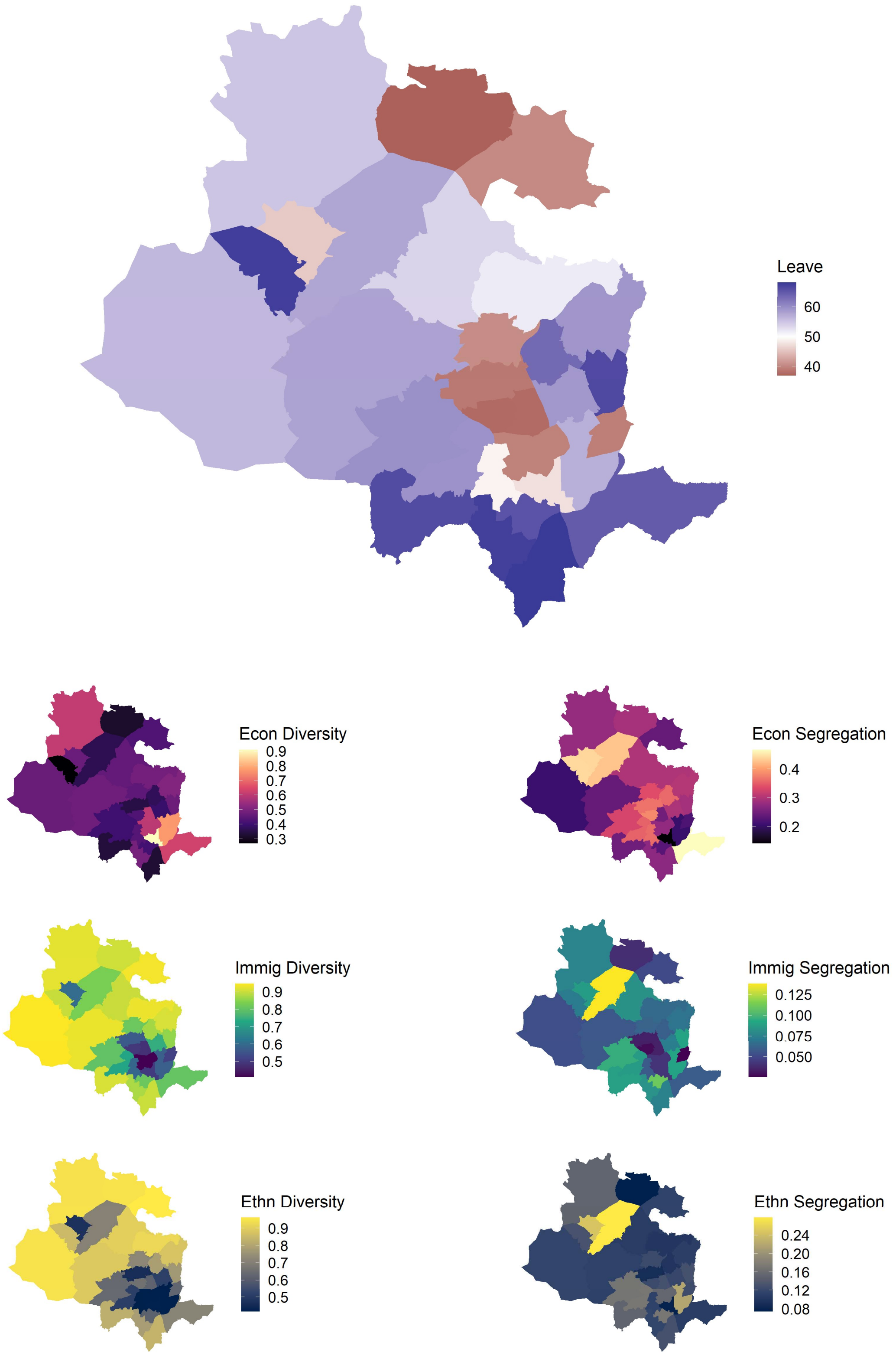


Figure 18: Ward-level Leave vote, diversity, and segregation (London)

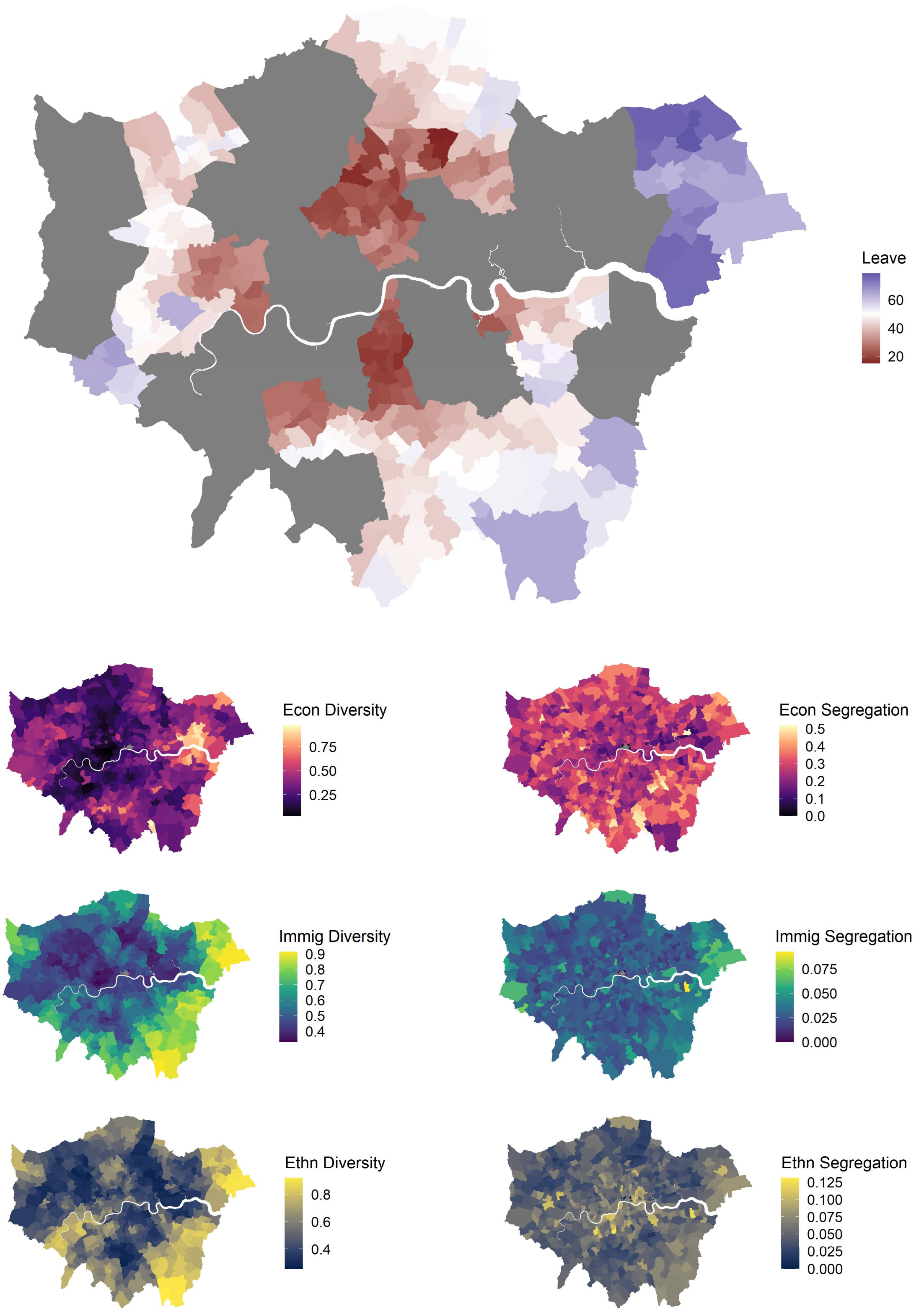
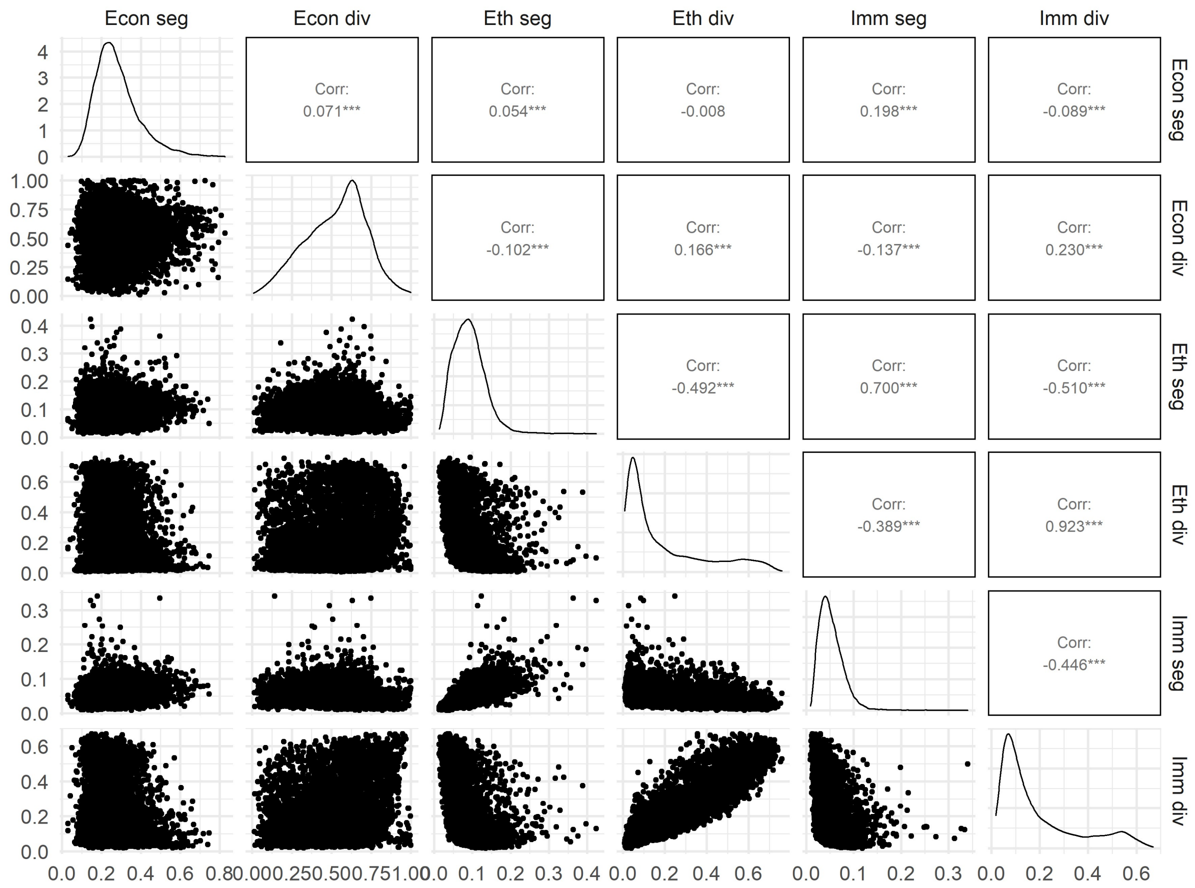


Figure 15: Correlation matrix for diversity and segregation measures, MSOA-level



6.3 Analytic strategy

I first examine between area relationships using data from the UK's Electoral Commission on the proportion of those voting Leave at the Local Authority District (LAD) level. LADs are relatively large spatial units (population M = 161,138, SD = 109,066), in some cases encompassing both urban and rural areas, and therefore not ideal for representing local contexts. Thankfully, some local authorities have released data on the referendum result for individual electoral Wards (N = 1,283). Wards are often commensurate with the neighbourhood level in terms of size, with the average population close to that of MSOAs (6,658). However, as noted earlier, Wards vary far more than MSOAs in terms of population (SD = 4,467, Min. = 136, and Max. = 33,937) and so do not always equate to the common sense definition of neighbourhoods. For this reason, I turn to MSOAs when looking at the individual-level.

I complement the aggregate-level vote data with a battery of control variables which have been shown to be important in other work on the determinants of Brexit. In particular, the area's average property price, population size, the percent of residents with no educational qualifications, the percent of residents not born in the UK, the change in the percent of residents not born in the UK (2001-2011), the growth in migrants from EU accession countries (2005-2015), the level of austerity cuts per worker, the percentage of residents who are old (60+), and the growth in mean hourly pay (2005-2015) (Ansell & Adler, 2019; Beatty & Fothergill, 2018; Becker et al., 2017; Fetzer, 2019; ONS, 2016). See Table A.20 and Table A.21 for descriptive statistics at the LAD and Ward levels, respectively. To estimate the relationship between diversity and segregation on aggregate vote Leave, I run simple OLS regressions including region fixed effects. Importantly, group-level behaviour might not correspond with individual behaviour – i.e. it might be subject to the ecological fallacy (see, for example, Kramer, 1983; Openshaw, 1984). Therefore, I also turn to individual-level data on support for Brexit.

For individual-level data, I use Wave 8 of Understanding Society (University of Essex & Research, 2019), the UK's large-scale household longitudinal survey (N = 34,272). Data was collected prior to and after the referendum on June 23rd 2016, and the survey included the exact same question posed in the referendum:

> "Should the United Kingdom remain a member of the European Union or leave the European Union?"

The survey provides relevant demographic information (age, education, gender, ethnicity, housing tenure), and, perhaps most importantly, the political party a respondent feels closest to, which proxies for political orientation and attitudes towards immigration (Kaufmann & Harris, 2015). I am therefore able to control for important individual differences that have been linked to support for Leave (see Becker et al. (2017) and Ansell & Adler (2019) for the importance of housing tenure). Table A.22 in the Annex provides descriptive statistics for the individual-level dataset. The survey also includes geographic identifiers, allowing me to place each respondent within their respective MSOA neighbourhood.

I model support for Brexit at the individual level using multilevel regression and restricted maximum likelihood estimation (via the `lme4` package in R; Bates et al. (2015)). Individuals are nested within neighbourhoods (defined in the base models as the MSOA-level). I also include fixed effects at the LAD level. This controls for any differences across these areas which might affect support for Brexit and relate to economic diversity and segregation, for example differences in austerity cuts and public service provision.

One of the major concerns with identifying the causal effect of diversity and segregation on voting behaviour is self-selection. Individuals are free to move to neighbourhoods populated with like-minded or ethnically-similar residents. Kaufmann & Harris (2015) provide an empirical analysis of migration patterns by political orientation using 19 waves of Understanding Society and its predecessor, the British Household Panel Survey. They find that self-selection should not be a concern given that moving to areas of less diversity is no more likely for those who can be considered to be anti-immigration. Other studies similarly find that self-selection is not a major concern, in both the UK (Gallego et al., 2016) and US (Cho et al., 2013). On the other hand, work by N. Lee et al. (2018) finds that residential immobility is a factor explaining support for Brexit.

I carry out additional analysis to mitigate selection concerns. First, I restrict the sample to those that have not moved for 20 years or more and to those living within a 5 mile radius of where they were living as adolescents (N = 9,210 and 2,312 respectively).

6.4 Results

6.4.1 Aggregate-level results

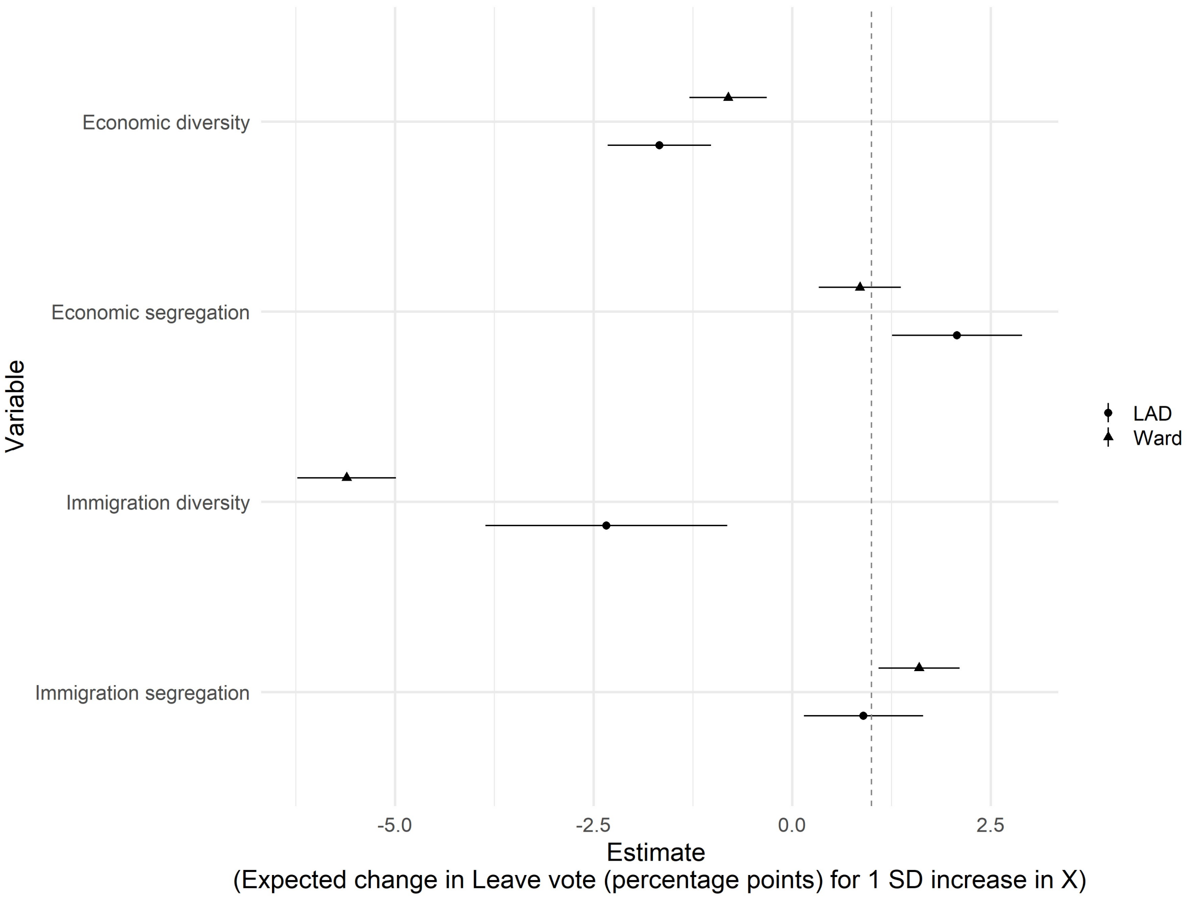
Figure 19 presents the standardised and exponentiated coefficients for the full LAD and Ward-level regressions. Both models include control variables and region fixed effects. The results indicate that diversity, both economic and in terms of country of origin, is statistically significant and negatively related to the Leave vote. Conversely, economic and social segregation is positively associated with the Leave vote. See the full results in Table A.23 of the Annex.

The coefficients are also substantive in size. A one standard deviation increase in economic diversity at the LAD-level is associated with a 1.67 percentage point decrease in the Leave vote. On the other hand, an increase in within-LAD economic segregation is expected to increase the Leave vote by 2.08 percentage points. In terms of immigrant diversity, a one standard deviation increase is expected to decrease the Leave vote by 2.34, whereas a one standard deviation increase in segregation is expected to increase the Leave vote by 0.9.

I repeat the same OLS between-area regressions at the Ward level. Although the data at the Ward-level is incomplete (not all LADs provide a Ward-level breakdown), the overall number of Wards exceeds that of LADs for a total of 1070. I am still able to control for the median property price (an indicator of average wealth), population size, percent of residents with no qualification, per cent of non-UK born residents and per cent of residents who are over 60 years old, but I can no longer control for hourly pay growth and the growth in migrants from EU accession countries.

The results are presented in Table A.24. I find similar results – more diversity is associated with higher support for Remain, while more segregation the opposite. In terms of substantiveness, the coefficient for immigration diversity is qualitatively larger, with a central estimate of -5.61, whereas the coefficient is equal to 1.6 for within-Ward country of origin segregation.

Figure 19: Standardised and exponentiated regression coefficients, between-area regressions for diversity and segregation on the Brexit vote



Note: OLS regression coefficients the effect of within-area economic and country of origin diversity and segregation on the Leave vote (%), England and Wales. Control variables include the Ward average property price (log scale), population size (log scale), the percent of adult residents with no qualification, the number of migrants (2011), the change in the number of migrants (2001-2011), the percent of the population aged 60+, and region fixed effects. All coefficients are exponentiated and standardised. Error bars are for 95% confidence level. See Table A.23 and Table A.24 for full results.

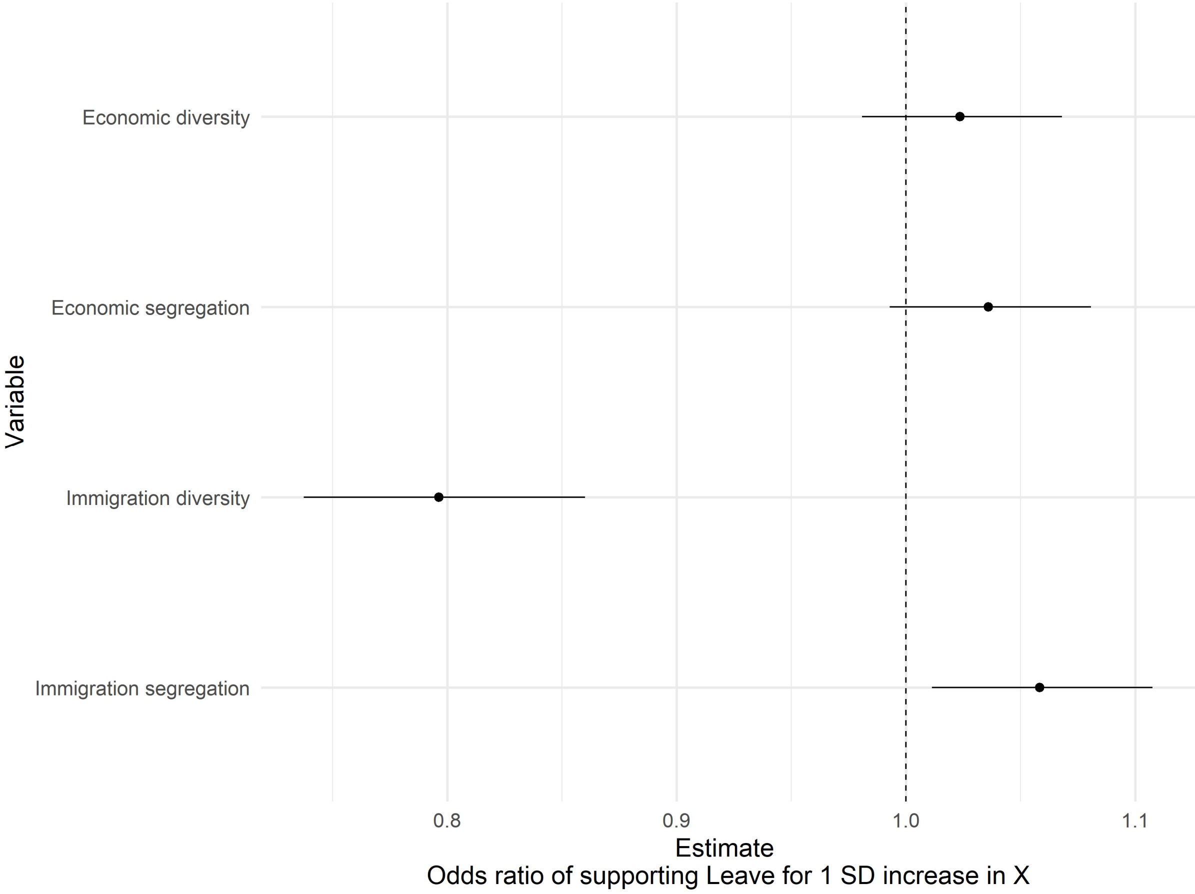
6.4.2 Individual-level results

I now turn to evaluating the effect of diversity and segregation on support for Brexit using individual-level data. Figure 20 provides the baseline results for the full model, i.e. including all diversity and segregation variables, controls, and fixed effects at the LAD level (see full results in Table A.25 in the Annex). I find that, as opposed to the between-area regression results, the coefficient on economic diversity and segregation are not significantly different from 0, once immigrant diversity and segregation are controlled for.

Conversely, I find that neighbourhood immigrant diversity and segregation are both significant and substantive in size. A one standard deviation increase in neighbourhood immigrant diversity is associated with an expected 20% reduction in the odds of supporting Brexit. On the other hand, a one standard deviation increase in segregation is associated with a 6% increase in the odds of supporting Brexit.

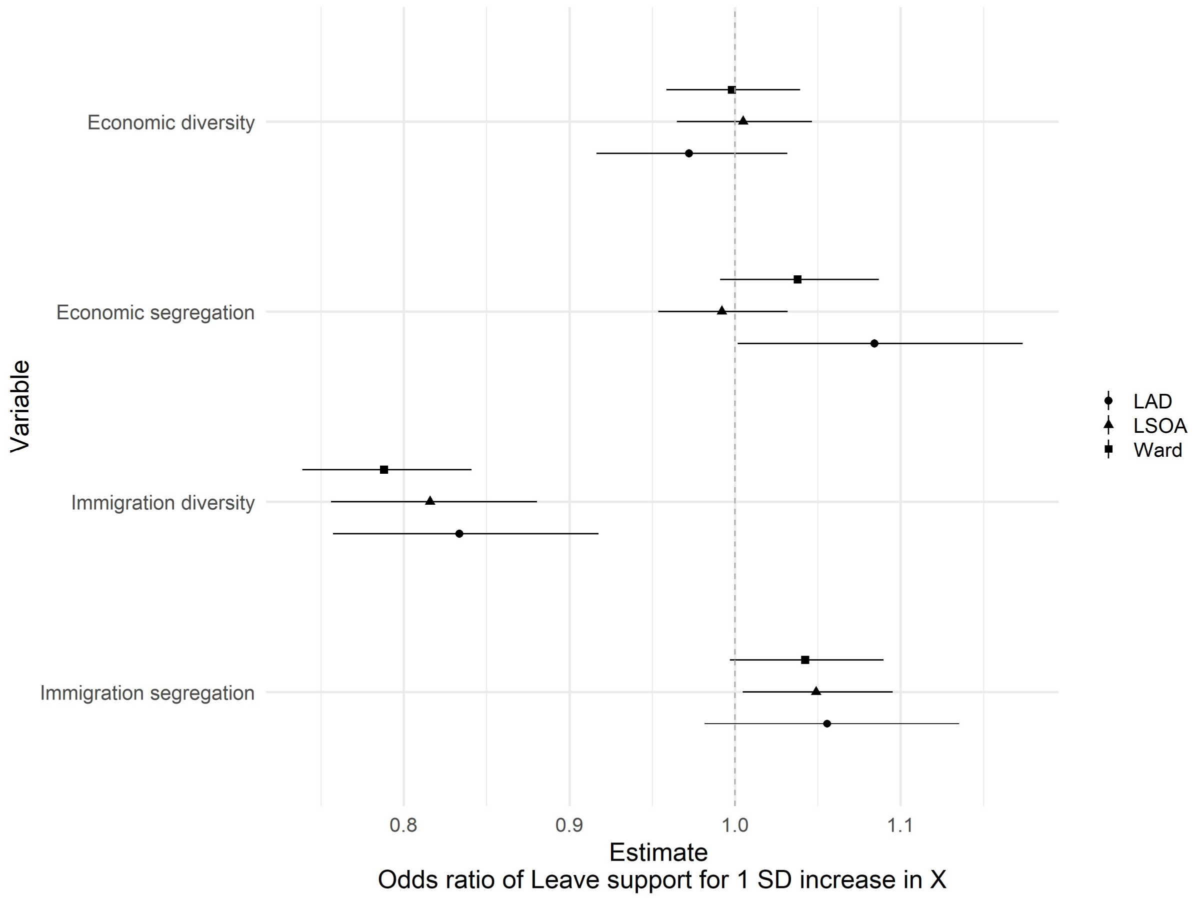
To verify the robustness of these results, and to mitigate concerns arising from the Modifiable Areal Unit Problem (Wong et al., 2012), I alter the geographical unit of analysis, both more disaggregated than MSOAs (LSOAs) and more aggregated (in alignment with the between-area regressions; Wards and LADs). Figure 21 provides the coefficient plot for these results. At the LSOA level, the estimates for both migrant diversity and segregation are similar, but at the aggregated levels only diversity remains significant, with an estimate that is broadly similar in size. In other words, immigrant diversity appears to reduce support for Brexit regardless of geographical level employed. This is contrary to work which finds that diversity exerts opposing effects at local and aggregated levels (Kaufmann & Harris, 2015; Tam Cho & Baer, 2011). On the other hand, the coefficient on immigrant segregation is attenuated above the MSOA level, becoming weaker at the Ward level ($\exp(\beta) = 1.04$, $p < 0.1$) and insignificant at the LAD level. While the economic variables were both insignificant at the MSOA level, economic segregation appears to have a negative effect on support for Leave at the LAD level ($\exp(\beta) = 1.08$, $p < 0.05$).

Figure 20: Effect of neighbourhood diversity and segregation on support for Brexit



Note: The figure provides coefficient estimates for a multilevel regression model of diversity and segregation on support for Brexit. Random intercepts are included at the MSOA level. Controls include: age, gender, education, ethnicity, political party support, household income, housing tenure, median housing value, and population density, as well as fixed effects at the LAD-level. All coefficient estimates are exponentiated and standardised. Error bars are for 95% confidence intervals. See full results in Table A.25 of the Annex.

Figure 21: Effect of neighbourhood diversity and segregation at different geographical levels on support for Brexit



Note: The figure provides coefficient estimates for a multilevel regression model of diversity and segregation on support for Brexit. Random intercepts are included at the LSOA, Ward, and LAD levels respectively. Controls include: age, gender, education, ethnicity, political party support, household income, housing tenure, median housing value, and population density, as well as fixed effects at the LAD-level. All variables are exponentiated and standardised. Error bars are for 95% confidence intervals. See full results in Table A.26 of the Annex.

6.4.3 Diversity, segregation and political party support

Next, I examine whether there is an interaction between party support, ethnic group, and household income and neighbourhood diversity and segregation. Table 18 provides the results. Interestingly, country of origin diversity appears to have a broad based effect, with no statistical difference between supporters of the Labour or Conservative party (the omitted category). Only the interaction term on the ‘Other’ party category – comprising the Liberal Democrats, Scottish Nationalist Party, Green Party, and other smaller political parties, is statistically significant and negative. In other words, greater diversity is expected to reduce support for Brexit across all political parties.

On the other hand, neighbourhood immigrant segregation appears to affect supporters of the Labour Party and the Other category. While the main term is indistinguishable from zero, The interaction term for both these categories are positive and statistically significant. At the mean value of segregation, a Labour supporter is expected to be 57% less likely to support Brexit relative to a supporter of the Conservatives, holding all other variables constant. However, if the Labour supporter is living in a neighbourhood that is two standard deviations above the mean in terms of segregation, they are expected to only be 37% less likely to support Brexit.

Table 18: Diversity and segregation interacted, MSOA-level

	Should UK leave EU?	
	Interacted with: Party support	
	(1)	(2)
Migrant Diversity	-0.196*** (0.049)	
Migrant Segregation		0.002 (0.031)
Age	0.329*** (0.018)	0.332*** (0.018)
Male	0.154*** (0.028)	0.152*** (0.028)
Degree	-0.656*** (0.030)	-0.656*** (0.030)
Household Income	-0.148*** (0.017)	-0.149*** (0.017)
Black	-0.180** (0.089)	-0.135 (0.089)
Other	-0.151 (0.103)	-0.102 (0.103)
White	0.253*** (0.062)	0.342*** (0.059)
Own	-0.121*** (0.039)	-0.130*** (0.039)
Rent Private	0.186*** (0.043)	0.160*** (0.043)
Rent Social	0.458*** (0.060)	0.445*** (0.060)
Labour	-0.851*** (0.038)	-0.848*** (0.037)
Other	-0.642*** (0.040)	-0.631*** (0.039)
UKIP	1.802*** (0.096)	1.856*** (0.086)
Median property value	-0.234*** (0.037)	-0.201*** (0.037)
Population density	0.010 (0.029)	-0.027 (0.029)
Migrant Diversity : Labour	-0.003 (0.040)	
Migrant Diversity : Other Party	-0.122*** (0.044)	
Migrant Diversity : UKIP	-0.029 (0.122)	
Migrant Segregation : Labour		0.094*** (0.036)
Migrant Segregation : Other Party		0.124*** (0.038)
Migrant Segregation : UKIP		-0.135 (0.082)
Constant	0.937** (0.454)	1.017** (0.453)
Random Intercept	MSOA	MSOA
Fixed Effects	LAD	LAD
Observations	27,984	27,984
Log Likelihood	-16,059.720	-16,071.910
Akaike Inf. Crit.	32,853.450	32,877.830
Bayesian Inf. Crit.	35,877.300	35,901.680
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Random intercept regression of support for Brexit on diversity and segregation interacted with political party support.	
	All explanatory variables are standardised. Standard errors are in parentheses.	

6.4.4 Additional robustness checks

I perform a number of additional checks to see whether the results hold. First, in order to mitigate concerns around self-selection into neighbourhoods, I restrict the sample to only those that have lived at the same address for at least 20 years. Second, I saturate the multilevel model with additional controls, in particular I add further contextual variables at the neighbourhood level – the local unemployment rate, the percent of adult residents with no qualification, the percent working in manufacturing industries and financial industries, the concentration of housing tenure (using the HHI), and finally the percent of houses in the local area which are socially rented (Ansell & Adler, 2019). None of these additional checks affect the findings with respect to country of origin diversity and segregation – see Table A.27 in the Annex for these additional robustness checks.

6.5 Discussion and conclusion

The decision by the UK electorate to Leave the EU has had monumental and historic implications. What drove voters to vote in the way they did? The current literature has constructed two narratives to answer this question. First, the 'left behind' narrative suggests that widening economic inequality induced a backlash amongst those on the losing end. Second, the cultural narrative argues that voting Brexit constituted a reaction against increased ethnic diversity and immigration.

In this paper, I dig deeper into these narratives by exploring how local levels of economic and ethnic diversity and segregation affects support for Brexit. In so doing, I build on a growing body of work which explores how neighbourhood composition affects political attitudes, in particular support for far-right or populist parties (Bowyer, 2008; see, for example, Evans & Ivaldi, 2020; Savelkoul et al., 2017; Vasilopoulos et al., 2021). My contributions to this body of work are two-fold. First, I am the first to examine this in relation to Brexit at multiple geographic levels, with a focus on the neighbourhood level. Second, I also explore economic diversity and segregation, exploiting a unique data on housing values at the neighbourhood level in the UK.

Taken together, the findings suggest that if the economic inequality and cultural backlash stories are indeed important drivers of Brexit support, then it appears that this does not result from within local-area exposure to inequality and immigrants. Rather, the results presented here suggest the reverse. I find that economic and country of origin diversity (segregation) decreases (increases) support for Brexit, albeit the findings for the country of origin diversity are the most consistent, existing at a range of levels and across specifications.

While at a first glance these results might seem inconsistent with the narratives surrounding Brexit, they might instead be compatible and suggest that the backlash is likely operating across geographical areas in the UK rather than within (see Evans & Ivaldi, 2020 for evidence of this with populist voting in France). This makes sense from the perspective of contact theory – prejudices against immigrants or the wealthy is harder to sustain if you regularly come into contact with representatives of this category, especially if that contact is in the form of friendships (Brannon & Walton, 2013; Pettigrew & Tropp, 2006). Enhanced knowledge, reduced anxiety and increased empathy and perspective taking are all understood to represent pathways through which contact reduce prejudice (Pettigrew & Tropp, 2006). On the other hand, if you live in areas that are more economically and ethnically homogeneous, and if those areas have seen absolute and relative economic decline (Bolet, 2021; Carreras et al., 2019), then it might be easier easier to blame the 'elite' or immigrants.

While individuals voted to Leave the EU for a multitude of reasons, it is clear from other research that anti-immigration sentiment was an important determinant (Stockemer et al., 2018; Vlandas, 2016). From that perspective, the findings here might suggest that contextual diversity – by promoting positive inter-group contact (Laurence & Bentley, 2018; Meleady et al., 2017) – contributed to reducing anti-immigrant sentiment, and thus support for Brexit along with it. However, given the constraints in the data – I unfortunately do not observe attitudes towards immigrants, instead proxying this by their political party support – future work might delve into the mechanisms behind these findings.

Moreover, contextual exposure to diversity is (obviously) not randomly assigned. I thus stop short of declaring that these relationships are causal, but I note that it does not appear that the results are driven by self-selection – the results hold when restricting the sample to those that are relatively immobile, either living within a short distance of where they grew up or at the same address for over 20 years (see also Kaufmann & Harris, 2015). While randomly assigning inter-group contact in a lab or field setting is unlikely to match real-life inter-group contact, quasi-experimental designs might be able to shed further light on the causal mechanisms at play.

Overall, the work presented here provides insight into the role of neighbourhood composition in shaping support for Brexit. These insights not only help to uncover the drivers of the outcome of this important referendum, but also shed light on how place feeds into political behaviour more broadly.

6.6 Annex

Table A.20: Descriptive statistics, LAD-level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Leave (%)	380	53.141	10.416	21.380	47.158	60.360	75.560
Economic Diversity	380	0.532	0.117	0.243	0.452	0.594	0.923
Economic Segregation	380	0.369	0.090	0.082	0.304	0.422	0.644
Immigrant Diversity	348	0.177	0.132	0.039	0.086	0.208	0.618
Immigrant Segregation	348	0.088	0.037	0.032	0.061	0.108	0.233
Average Property Price	380	296,763.600	183,624.600	102,347.600	178,685.900	352,005.000	2,018,094.000
Population	348	161,112.900	109,013.900	2,203.000	93,888.000	199,823.200	1,071,722.000
No qualifications %	380	20.579	7.835	0.171	17.600	25.400	36.000
Non-UK born %	380	0.115	0.033	0.065	0.094	0.123	0.260
Non-UK born change	348	-4.684	11.396	-39.575	-12.235	1.759	33.010
Migrant EU Accession growth	380	0.017	0.017	-0.004	0.007	0.020	0.121
Austerity cuts / worker	378	447.780	121.925	177.000	340.000	534.500	914.000
Over 60 %	380	0.240	0.050	0.084	0.214	0.274	0.380
Mean hourly pay growth	380	0.231	0.161	-0.238	0.177	0.275	2.899

Table A.21: Descriptive statistics, Ward-level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Leave (%)	1,283	52.34	14.30	12.16	43.09	63.83	82.51
Economic Diversity	8,334	0.53	0.18	0.004	0.39	0.66	1.00
Economic Segregation	8,334	0.25	0.12	0.00	0.16	0.31	0.76
Immigrant Diversity	7,981	0.15	0.14	0.02	0.06	0.18	0.67
Immigrant Segregation	7,981	0.05	0.03	0.00	0.03	0.07	0.36
Average Property Price	8,350	298,251.80	198,610.20	58,809.79	173,210.60	365,321.70	3,547,146.00
Population	7,981	6,657.93	4,467.15	136.00	3,294.00	8,971.00	33,937.00
No qualifications %	6,499	21.47	8.83	0.06	16.50	27.00	54.80
Non-UK born %	8,334	0.11	0.06	0.04	0.08	0.12	0.71
Non-UK born change	7,981	-2.27	23.16	-83.96	-16.56	10.51	297.83
Over 60 %	6,499	0.25	0.08	0.01	0.20	0.30	0.68

Table A.22: Descriptive statistics, individual-level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Leave support	34,272	0.42	0.49	0.00	0.00	1.00	1.00
Economic Diversity	36,724	0.52	0.18	0.01	0.39	0.65	1.00
Economic Segregation	36,724	0.27	0.10	0.03	0.20	0.32	0.83
Migrant Diversity	33,526	0.21	0.18	0.02	0.07	0.33	0.66
Migrant Segregation	33,526	0.05	0.03	0.01	0.03	0.06	0.34
Age	39,275	48.78	18.73	16.00	34.00	63.00	102.00
Male	39,289	0.46	0.50	0	0	1	1
Degree	38,431	1.38	0.49	1.00	1.00	2.00	2.00
Household Income	38,769	4,062.53	2,912.84	0.00	2,029.16	5,338.17	86,065.62
White	38,970	0.81	0.39	0.00	1.00	1.00	1.00
Own	38,488	0.71	0.45	0.00	0.00	1.00	1.00
Labour	22,670	0.57	0.50	0.00	0.00	1.00	1.00
Median property value	36,715	251,370.90	150,880.60	52,997.81	140,974.10	322,997.50	2,197,955.00
Ln(Population density)	36,724	2.75	1.62	-3.90	1.90	3.85	5.51

Table A.23: Between LAD regression

	Leave vote (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic Diversity	-1.278***		-1.665***				-1.673***
	(0.338)		(0.336)				(0.330)
Economic Segregation		1.622***	2.103***				2.076***
		(0.423)	(0.420)				(0.417)
Immigrant Diversity				-1.687**		-2.183***	-2.339***
				(0.803)		(0.818)	(0.774)
Immigrant Segregation					0.801**	1.049***	0.897**
					(0.394)	(0.402)	(0.381)
Average Property Price	0.007	-0.727	0.492	-0.547	-0.866*	-0.415	0.997*
	(0.514)	(0.457)	(0.505)	(0.490)	(0.463)	(0.489)	(0.524)
Population	-1.317***	-1.564***	-1.490***	-1.298***	-1.504***	-1.389***	-1.438***
	(0.286)	(0.288)	(0.279)	(0.294)	(0.294)	(0.294)	(0.280)
No qualifications %	11.384***	11.220***	10.938***	11.381***	10.739***	10.301***	9.851***
	(0.987)	(0.989)	(0.957)	(1.004)	(1.075)	(1.077)	(1.020)
Non-UK born %	-2.438***	-1.946***	-2.213***	-1.893***	-2.306***	-1.974***	-1.962***
	(0.356)	(0.355)	(0.347)	(0.380)	(0.360)	(0.378)	(0.367)
Non-UK born change	-0.724**	-0.971***	-0.792***	-0.854***	-0.868***	-0.828***	-0.736**
	(0.316)	(0.314)	(0.305)	(0.318)	(0.318)	(0.315)	(0.301)
Migrant EU Accession growth	0.591*	0.841***	0.734**	1.186***	0.645**	1.251***	1.333***
	(0.322)	(0.323)	(0.312)	(0.398)	(0.327)	(0.396)	(0.377)
Austerity cuts / worker	-1.357***	-1.600***	-1.641***	-1.289**	-1.235**	-1.076**	-1.355***
	(0.517)	(0.520)	(0.502)	(0.527)	(0.530)	(0.528)	(0.503)
Over 60 %	-0.122	0.664	0.686*	-0.416	0.133	-0.382	0.219
	(0.369)	(0.405)	(0.391)	(0.424)	(0.378)	(0.421)	(0.425)
Mean hourly pay growth	-0.884*	-0.904*	-1.104**	-0.793	-0.606	-0.599	-0.972**
	(0.501)	(0.501)	(0.486)	(0.508)	(0.514)	(0.509)	(0.485)
Constant	52.217***	53.347***	52.867***	52.728***	53.179***	53.322***	53.362***
	(0.825)	(0.829)	(0.807)	(0.826)	(0.856)	(0.850)	(0.819)
Region fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	346	346	346	346	346	346	346
R^2	0.817	0.817	0.830	0.811	0.811	0.815	0.836
Adjusted R^2	0.806	0.806	0.819	0.800	0.800	0.804	0.825
Residual Std. Error	4.315 (df = 326)	4.313 (df = 326)	4.164 (df = 325)	4.379 (df = 326)	4.381 (df = 326)	4.340 (df = 325)	4.101 (df = 323)
Note:	*p<0.1; **p<0.05; ***p<0.01						

Table A.24: Between Ward regression

	Leave vote (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic Diversity	-0.582**		-0.808***				-0.806***
	(0.288)		(0.289)				(0.248)
Economic Segregation		1.282***	1.425***				0.852***
		(0.302)	(0.306)				(0.264)
Immigrant Diversity				-5.991***		-5.685***	-5.607***
				(0.320)		(0.318)	(0.316)
Immigrant Segregation					2.345***	1.639***	1.598***
					(0.292)	(0.259)	(0.259)
Average Property Price	-4.935***	-5.111***	-4.648***	-4.366***	-5.094***	-4.298***	-3.771***
	(0.392)	(0.358)	(0.393)	(0.315)	(0.349)	(0.309)	(0.339)
Population	-2.601***	-2.787***	-2.767***	-1.839***	-2.360***	-1.692***	-1.774***
	(0.256)	(0.256)	(0.256)	(0.226)	(0.251)	(0.223)	(0.224)
No qualifications %	6.280***	6.276***	6.262***	6.552***	5.561***	6.029***	6.017***
	(0.382)	(0.380)	(0.379)	(0.332)	(0.383)	(0.337)	(0.334)
Non-UK born %	-1.216***	-1.226***	-1.205***	-0.270	-1.687***	-0.639**	-0.620**
	(0.318)	(0.316)	(0.315)	(0.281)	(0.315)	(0.282)	(0.280)
Non-UK born change	-1.088***	-0.976***	-0.952***	-0.681***	-1.078***	-0.689***	-0.604**
	(0.292)	(0.291)	(0.290)	(0.254)	(0.284)	(0.250)	(0.249)
Over 60 %	4.364***	4.200***	4.231***	0.475	3.934***	0.395	0.411
	(0.409)	(0.407)	(0.406)	(0.410)	(0.400)	(0.403)	(0.400)
Constant	53.348***	53.180***	53.079***	54.190***	54.334***	54.800***	54.549***
	(0.705)	(0.701)	(0.700)	(0.613)	(0.695)	(0.609)	(0.608)
Region fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	1,070	1,070	1,070	1,070	1,070	1,070	1,070
R^2	0.743	0.746	0.748	0.806	0.757	0.813	0.816
Adjusted R^2	0.739	0.743	0.744	0.803	0.753	0.810	0.813
Residual Std. Error	7.396 (df = 1054)	7.348 (df = 1054)	7.324 (df = 1053)	6.420 (df = 1054)	7.194 (df = 1054)	6.304 (df = 1053)	6.257 (df = 1051)
Note:	*p<0.1; **p<0.05; ***p<0.01						

Table A.25: Effect of neighbourhood diversity and segregation on support for Brexit, Individual-level

	Should UK leave the EU?				
	(1)	(2)	(3)	(4)	(5)
Economic Diversity	0.027	0.017			0.023
	(0.020)	(0.020)			(0.022)
Economic Segregation		0.060***			0.035
		(0.020)			(0.022)
Migrant Diversity			-0.235***	-0.233***	-0.228***
			(0.039)	(0.039)	(0.039)
Migrant Segregation				0.062***	0.057**
				(0.023)	(0.023)
Age	0.323***	0.323***	0.329***	0.329***	0.328***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Male	0.177***	0.177***	0.153***	0.154***	0.154***
	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)
Degree	-0.638***	-0.638***	-0.655***	-0.654***	-0.654***
	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Household Income	-0.152***	-0.153***	-0.148***	-0.149***	-0.149***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
Black	-0.154*	-0.160*	-0.180**	-0.181**	-0.185**
	(0.088)	(0.088)	(0.089)	(0.089)	(0.089)
Other	-0.125	-0.128	-0.161	-0.165	-0.166
	(0.102)	(0.102)	(0.103)	(0.103)	(0.103)
White	0.329***	0.319***	0.248***	0.239***	0.236***
	(0.058)	(0.058)	(0.061)	(0.061)	(0.061)
Own	-0.122***	-0.122***	-0.123***	-0.121***	-0.122***
	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)
Rent Private	0.166***	0.169***	0.183***	0.183***	0.183***
	(0.041)	(0.041)	(0.043)	(0.043)	(0.043)
Rent Social	0.443***	0.440***	0.456***	0.458***	0.456***
	(0.056)	(0.056)	(0.060)	(0.060)	(0.060)
Labour	-0.860***	-0.860***	-0.838***	-0.838***	-0.838***
	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)
Other	-0.607***	-0.606***	-0.622***	-0.621***	-0.621***
	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)
UKIP	1.794***	1.794***	1.809***	1.810***	1.810***
	(0.082)	(0.082)	(0.083)	(0.083)	(0.083)
Median property value	-0.218***	-0.203***	-0.231***	-0.218***	-0.225***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.039)
Population density	-0.006	-0.017	0.011	0.019	0.015
	(0.025)	(0.025)	(0.029)	(0.030)	(0.030)
Constant	1.069**	1.032**	0.915**	0.855*	0.834*
	(0.454)	(0.454)	(0.454)	(0.454)	(0.454)
Random Intercept	MSOA	MSOA	MSOA	MSOA	MSOA

Fixed Effects	LAD	LAD	LAD	LAD	LAD
Observations	30,842	30,842	27,984	27,984	27,984
Log Likelihood	-17,682.820	-17,677.870	-16,065.990	-16,062.180	-16,059.830
Akaike Inf. Crit.	36,157.650	36,149.740	32,859.970	32,854.360	32,853.670
Bayesian Inf. Crit.	39,458.950	39,459.380	35,859.110	35,861.740	35,877.520
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table A.26: Effect of neighbourhood diversity and segregation at different geographic levels on support for Brexit

	Should UK leave EU?		
	LSOA	Ward	LAD
	(1)	(2)	(3)
Economic Diversity	0.005 (0.021)	-0.002 (0.021)	-0.028 (0.030)
Economic Segregation	-0.008 (0.020)	0.037 (0.024)	0.081** (0.040)
Migrant Diversity	-0.203*** (0.039)	-0.238*** (0.033)	-0.182*** (0.049)
Migrant Segregation	0.048** (0.022)	0.042* (0.023)	0.054 (0.037)
Age	0.346*** (0.019)	0.328*** (0.018)	0.316*** (0.017)
Male	0.168*** (0.029)	0.154*** (0.028)	0.144*** (0.027)
Degree	-0.639*** (0.032)	-0.666*** (0.030)	-0.690*** (0.029)
Household Income	-0.157*** (0.019)	-0.145*** (0.017)	-0.157*** (0.016)
Black	-0.177* (0.096)	-0.196** (0.087)	-0.102 (0.082)
Other	-0.171 (0.110)	-0.181* (0.102)	-0.124 (0.097)
White	0.222*** (0.068)	0.205*** (0.059)	0.343*** (0.052)
Own	-0.129*** (0.043)	-0.126*** (0.039)	-0.150*** (0.036)
Rent Private	0.193*** (0.048)	0.186*** (0.043)	0.160*** (0.040)
Rent Social	0.475*** (0.066)	0.450*** (0.059)	0.453*** (0.055)
Labour	-0.848*** (0.040)	-0.848*** (0.036)	-0.827*** (0.034)
Other	-0.636*** (0.041)	-0.633*** (0.038)	-0.615*** (0.036)
UKIP	1.793*** (0.087)	1.793*** (0.083)	1.825*** (0.081)
Median property value	-0.161*** (0.033)	-0.199*** (0.032)	-0.075 (0.053)
Population density	0.010 (0.026)	0.026 (0.027)	0.007 (0.044)
Constant	1.043** (0.478)	0.174** (0.086)	0.119 (0.090)
Random Intercept	LSOA	Ward	LAD
Fixed Effects	LAD	Region	Region
Observations	27,970	27,984	27,992
Log Likelihood	-15,881.790	-16,309.460	-16,509.410
Akaike Inf. Crit.	32,497.580	32,678.910	33,078.820
Bayesian Inf. Crit.	35,521.250	32,926.090	33,326.010
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.27: Additional robustness checks

	Should UK leave the EU?		
	Lived in address 20+ years	Live within 5 miles of where grew up	Additional contextual controls
	(1)	(2)	(3)
Economic Diversity	-0.067	-0.086	0.023
	(0.041)	(0.093)	(0.022)
Economic Segregation	0.016	-0.027	0.030
	(0.041)	(0.078)	(0.022)
Migrant Diversity	-0.201***	-0.265*	-0.190***
	(0.076)	(0.143)	(0.046)
Migrant Segregation	0.096**	0.047	0.047**
	(0.044)	(0.113)	(0.023)
Age	0.224***	0.511***	0.328***
	(0.045)	(0.096)	(0.018)
Male	0.176***	0.205	0.155***
	(0.057)	(0.129)	(0.028)
Degree	-0.733***	-0.179	-0.640***
	(0.064)	(0.142)	(0.030)
Household Income	-0.122***	-0.201**	-0.148***
	(0.037)	(0.083)	(0.017)
Black	-0.126	-0.375*	-0.163*
	(0.197)	(0.199)	(0.089)
Other	0.097	-0.396	-0.140
	(0.253)	(0.264)	(0.103)
White	0.333**	-0.320	0.271***
	(0.138)	(0.212)	(0.062)
Own	-0.135	-0.201	-0.123***
	(0.083)	(0.183)	(0.039)
Rent Private	0.299**	0.282	0.186***
	(0.123)	(0.184)	(0.043)
Rent Social	0.344**	-0.149	0.431***
	(0.138)	(0.218)	(0.060)
Labour	-0.969***	-0.287	-0.842***
	(0.072)	(0.198)	(0.037)
Other	-0.705***	-0.329	-0.623***
	(0.083)	(0.229)	(0.039)
UKIP	1.958***	2.435***	1.803***
	(0.176)	(0.635)	(0.083)
Median property value	-0.070	-0.309**	-0.126**
	(0.069)	(0.156)	(0.049)
Population density	0.071	-0.061	-0.003
	(0.058)	(0.227)	(0.031)

Unemployed (%)			2.142
			(2.171)
No Qualification (%)			1.717***
			(0.425)
Manufacturing (%)			0.151
			(0.929)
Finance (%)			1.081
			(1.263)
Tenure Concentration (HHI)			0.057**
			(0.027)
Social Rented (%)			-0.0002
			(0.0005)
Constant	2.635**	19.831	0.040
	(1.157)	(10,754.150)	(0.492)
Random Intercept	MSOA	MSOA	MSOA
Fixed Effects	LAD	LAD	LAD
Observations	6,877	1,585	27,984
Log Likelihood	-3,904.419	-784.787	-16,040.080
Akaike Inf. Crit.	8,534.838	2,027.573	32,826.160
Bayesian Inf. Crit.	11,016.280	3,256.923	35,899.450
Note:	*p<0.1; **p<0.05; ***p<0.01		

7 Critical discussion and conclusion

Economic inequality is a topic that has been extensively studied in the social sciences. Recent years have seen a renewed emphasis on measurement, with scholars taking a local-perspective, operationalising inequality at relatively fine geographical resolutions and finding the impact of micro-manifestations of economic inequality to be important for individual behaviour and outcomes (see, for example, Chetty & Hendren, 2018b). This movement towards local inequality has happened primarily in the North America, where income data is provided as part of the census. Some countries, notably the UK, do not collect extensive income information from its residents, thereby making it impossible to reliably measure economic inequality at the local level.

In Chapter 2, I remedy this important measurement gap by exploiting a large, unique dataset on the value of over 26 million UK residences. This data makes it possible to measure economic inequality in the UK at a hyper-local level for the first time, allowing me to describe neighbourhood-level variation in inequality. Importantly, I evaluate whether neighbourhood housing value inequality is a salient measure of economic inequality using the British Election Study and a representative survey of UK respondents. I show that this is indeed the case – housing value inequality is associated with perceptions of income inequality. This conclusion is buttressed by textual responses – local housing discrepancies are frequently mentioned as being a key feature used by individuals to estimate neighbourhood inequality. In other words, seeing housing value inequality affects people's beliefs about local economic inequality. I then examine the patterns of local inequality for the whole of the UK, from the city down to the neighbourhood level. I find 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 *unequal*.

In Chapter 3, I turn to analysing of the determinants of neighbourhood and urban inequality for the UK. I find that, while there are commonalities across spatial levels, there are also important differences in the factors driving higher inequality, notable amenities and the unemployment rate. Chapter 3 is the first paper investigates the determinants of inequality at the neighbourhood level in the UK, thereby providing useful insights for policymakers and urban planners interested in neighbourhood dynamics. Moreover, taken together with Chapter 2, the analysis is important in that it provides insight into how local inequality is experienced in a multifaceted fashion. In other words, neighbourhood inequality is not simply marked by economic discrepancies, but also by heterogeneous ethnic backgrounds, education levels, and housing tenures, as well as in terms of the sorts of amenities that are present. This advances our understanding of the lived experiences of inequality and can help inform future work on the implications of neighbourhood inequality for individual and social outcomes.

Chapters 4 to 6 use the measure developed in Chapter 2 to shed light on the consequences of inequality. In particular, Chapter 4 aims to clarify what effect inequality has on pro-social behaviour, both the main effect and when interacted with income. Chapter 5 seeks to understand why police stop and search activity persists even though the empirical evidence suggests it doesn't mitigate crime, taking a spatial perspective. And, finally, Chapter 6 explores whether economic inequality, operationalised through a related measure – diversity, along with ethnic diversity affect political outcomes, using Brexit as the case study. These chapters therefore cover a range of individual and group behaviours, from the private to the civic spheres.

I find that the consequences of inequality are both positive and negative depending on the behaviour analysed. On the positive side, Chapter 4 provides strong evidence that local inequality leads to more generosity, especially for higher income individuals and households. On the other hand, local inequality is associated with a substantively higher number of police stops and searches without clear evidence that this policy reduces or deters crime. Local economic (and ethnic) heterogeneity also appears to reduce support for Brexit, suggesting that anti-immigrant sentiment is lessened through inter-group contact. In sum – the answer to the question of whether local inequality is good or bad is: it depends.

Importantly, across the various papers of this thesis, I take a multi-scalar approach to measuring inequality and evaluating its consequences. Rather than focus on one geographic level, I either verify the robustness of the results by looking at how they vary when taking a more granular or aggregated perspective (e.g. Chapter 6 on Brexit), or I explicitly compare findings at different geographical levels (e.g. Chapter 3 on the determinants of local inequality). This is typically not done in empirical research which explores the consequences of economic inequality. Instead, oftentimes the choice of spatial level is made without justification or out of convenience (e.g. data availability). As a result, there is usually no critical discussion as to the theoretical pathways through which inequality at the chosen level might affect outcomes. Not explicitly considering whether the spatial scale is appropriate potentially weakens the analysis (e.g. selecting the macro-scale when a more localised level would be more appropriate), and there could be concerns around the Modifiable Areal Unit Problem (Wong et al., 2012). For example, as covered in Chapter 4, Côté et al. (2015) and Schmukle et al. (2019) do not comment on why the macro-level is appropriate for investigating the effect of inequality on pro-social behaviour, and there are good theoretical reasons to suspect that local inequality might matter more, i.e. contact theory (Allport et al., 1954).

Furthermore, as this thesis demonstrates across papers, and as others have also shown elsewhere (Ifcher et al., 2019; B. A. Lee et al., 2008; Reardon et al., 2008; e.g. Vasilopoulos et al., 2021) the contextual variable of interest might have opposing effects depending on whether it is operationalised at the neighbourhood, local authority, or national level. Indeed, this seems to be the case for pro-social behaviour, with some evidence presented here (Chapter 4) that state-level inequality does exert a negative effect on the extensive margin of charitable giving, whereas at the local level the opposite is true. On the other hand, Chapter 6 shows that country of origin diversity is substantively negatively associated with support for Brexit, and this result holds regardless of the spatial level chosen, from the LSOA up to the Local Authority level.

That said, there are still a number of limitations to note regarding the selection of spatial levels in this thesis. First, neighbourhoods are by definition subjective and contingent on individual conceptualisation. While the LSOA/MSOA boundaries are meant to align with natural boundaries (e.g. bounded by major roads), it is not clear whether they conform to individual conceptions. Ideally, studies investigating the effects of local inequality would construct 'ego-centric' neighbourhoods (B. A. Lee et al., 2019), for example by defining specific neighbourhoods for each individual according to subjective maps (Campbell et al., 2009; Catney et al., 2019; Pinchak et al., 2020; Wong et al., 2012), revealed patterns of behaviour (Athey et al., 2020; Louail et al., 2014), or a set radius (e.g. 400m; Duncan et al. (2014); Hartung & Hillmert (2019)).

Second, the main definition of UK neighbourhood used in this thesis varies across papers. In some papers, it is taken as the LSOA level, while in others it is the more spatially aggregated

MSOA. The differing conceptualisations are used mainly to align multiple sources of data (e.g. the MSOA-level is close in size to the Ward-level, for which there is data on the Brexit vote – see Chapter 6). As the default, however, I choose to focus on the LSOA – e.g. see the description of patterns of economic inequality in Chapter 2, and where the MSOA is used as the base neighbourhood, I verify that the results hold also for the LSOA level where possible – see Chapters 4 and 6, and Section 2.4.

Third, given this thesis focuses on one country – the UK, it is not clear whether the findings can be generalised to other national contexts. The sole exception is regarding the relationship between pro-social behaviour and local inequality – Chapter 8 presents evidence from the US alongside the UK. The UK (and US) have relatively high levels of inequality, as well as specific institutional and cultural contexts, compared with other developed nations. This therefore suggests that cross-county comparative analysis is warranted to establish how these national-level attributes might affect the empirical findings presented here.

The UK might also differ in important ways from other countries with regards sub-national patterns of inequality, for example as result of urban and social housing policy which results in distinctive patterns of economic segregation or integration across neighbourhoods. This calls for further research to compare UK with other countries, for example by replicating the findings of Chapter 2 and Chapter 3 for other countries, ideally with comparable local inequality measures down to the neighbourhood-level for different contexts.

The other papers in this thesis can also be built on through further research to address the point on generalisability. For example, an obvious next step would be to try to replicate the results on police stop and search behaviour presented in Chapter 5 using data from other countries where police hold similar powers (e.g. the US). While the Chapter 4 on pro-social behaviour covers both the UK and US, the findings could in principle be broadened to many more countries where sufficiently granular micro data on inequality and charitable giving is available. And finally, though the findings presented in Chapter 6 can be situated within an existing literature which investigates the role of inequality and ethnic heterogeneity on anti-immigrant or far-right sentiment in different countries (Bowyer, 2008; see, for example, Evans & Ivaldi, 2020; Savelkoul et al., 2017; Vasilopoulos et al., 2021), there is still more work to be done in this area, particularly as the rise in populism does not appear to be abating in many countries around the world as of this writing.

The thread running through this thesis is that local contexts matter. Specifically, the level of neighbourhood inequality has consequences. However, neighbourhood inequality is unlikely the only relevant experience individuals have with inequality. Indeed, as briefly discussed in 2.4, information affecting people's perceptions of local and national inequality likely come from a number of sources, with local contexts being only one influence. Other sources are likely to be the media, and social networks (which are only partly influenced by neighbourhoods). Moreover, individuals commute to work (e.g. going from Luton to London everyday), travel for other reasons, both within urban areas and internationally, and thereby absorb far more information about inequality than what they are exposed to within the neighbourhoods they live in. My claim in this thesis is not that local contexts are the only influence, nor that they are the most important influence, just that they are an influence. The findings across papers clearly testify to this, contributing to our understanding of the consequences of local inequality.

However, while I conduct a number of robustness checks in each paper to mitigate endogeneity concerns, for example restricting the data to those that live within the same 5 mile radius of where they grew up (Chapter 4), I nevertheless do not have randomly assigned local inequality in any of the studies, nor do I have quasi-experimental data. Therefore, a general weakness of this thesis is a lack of clear-cut causal identification. While there is a large literature which varies inequality in artificial lab settings, it is not clear that these experiments adequately represent the real-world, both in terms of inequality exposure and the behaviours studied (see Galizzi & Navarro-Martínez, 2019 for social preference games in particular). This, therefore, means that future work is warranted, in particular that which can exploit naturally occurring exogenous variation in inequality, or that utilises compelling instruments to shed light on the consequences of local inequality for individuals and society.

More generally, future work could use the measures and data developed for this thesis to answer other important research questions related to the determinants or consequences of local inequality. Indeed, I have made the inequality data available online for download here: https://github.com/jhsuss/uk-local-inequality. While the data is available for the UK, similar sorts of contextually and perceptually-relevant data might be used to explore neighbourhood-level inequality in other countries.

The contexts within which people spend much of their lives, the neighbourhoods and environments where they act and react are important influences on their lived experiences. Economic discrepancies manifest and social comparison processes happen at the micro-level, and therefore understanding inequality's effects on important economic, political and social behaviours requires corresponding measurement. In exploring the patterns, the determinants and (some of) the consequences of economic disparities within neighbourhoods in the UK in this thesis, I provide conclusive evidence of the need to and the benefits of examining economic inequality at the local level.

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