Inequality and Support for Right-wing Populism in Britain*

Zachary P. Dickson
London School of Economics
z.dickson@lse.ac.uk

Sara B. Hobolt
London School of Economics
s.b.hobolt@lse.ac.uk

Abstract

The rise of right-wing populism is a defining feature of contemporary politics. The literature explaining this phenomenon often points to either economic grievances or a backlash against cultural change. Crucial to both explanations, we argue, are feelings of relative status threat and perceived inequality that fuel resentment and lead to support for politicians who promise to protect the interests of aggrieved populations. We test this argument in the United Kingdom by examining the effects of localized wealth inequality—proxied by housing values—on support for the populist right. We assemble a novel large-scale dataset that includes the universe of house price transactions from 1995-2022, and use machine learning methods to estimate the dynamic value of the majority of residential property in the nation. After constructing small-area spatio-temporal estimates of house price inequality, we leverage staggered difference-in-differences and instrumental variables designs to estimate the effects of inequality on local support for populist right parties using local electoral data and survey panel data. Across multiple analyses, our results demonstrate that salient, localized inequality increases support for populist right parties. These findings lend further support for the cultural origins of right-wing populism.

*2025 EPSA Draft

Acknowledgments: Thanks for helpful comments go to the brilliant folks at the LSE Political Behaviour Work-in-Progress seminar. We also thank the University of Glasgow Urban Big Data Centre (UBDC) for providing access to housing data from Zoopla.

Introduction

The rise of right-wing populist parties in Europe and beyond has sparked significant scholarly debate. A large literature has argued that this trend represents a backlash against globalization, where victims of economic dislocation, created by cross-border trade and technological progress, rebel against their marginalization and economic insecurity by supporting the populist right (e.g. Colantone and Stanig 2018; Walter 2021; Scheiring et al. 2024; Guiso et al. 2024). Scholars argue that globalization, technological change, and labor market disruptions have eroded economic security for the "left behind", fostering widespread discontent and a loss of trust in mainstream political parties (Rodrik 2021; Anelli, Colantone, and Stanig 2021). According to this view, economic "losers" turn to populist parties that promise to protect their interests through trade protectionism, restrictions on migration, or opposition to supranational governance (Colantone and Stanig 2019).

While this account highlights the important role of structural transformations in explaining populism, research has also shown that there is not a simple relationship between economic inequality, precarity and support for the populist right. As Margalit (2019) concludes in his review of the literature on the causes of populism: "the empirical evidence put forth to date does not establish that populism is predominantly an outcome of a rise in economic insecurity." Indeed, empirical studies show that economic precarity or low income alone do not strongly predict support for populist right parties (Gidron and Mijs 2019; Ciccolini 2021) or populist causes such as Brexit (Hobolt 2016). Whereas subjective perceptions of economic insecurity is strongly associated with populist right voting (Gidron and Hall 2017; Cramer 2016; Bonikowski 2017), there is much less clear evidence when it comes to objective indicators of economic precarity and populist right support (Gidron and Mijs 2019; Margalit 2019). Instead, cultural factors – such as national identity concerns, opposition to immigration, and perceived threats to traditional values – often hold greater explanatory power in understanding why voters align with the radical right (Norris and Inglehart 2019).

These economic and cultural approaches to explaining populist right support are often presented as competing accounts of support for the populist right, yet we argue that a key mechanism common to both approaches are feelings of relative status loss. Specifically, we argue that perceived inequality fuels resentment and leads to support for parties who promise

to protect the interests of aggrieved populations. Building on the literature on social status decline (Gidron and Hall 2017; Bonikowski 2017; Kurer and Gallego 2019; Kurer 2020), we shift our focus from absolute material deprivation to localized inequality, arguing that a key driver of support for the radical right are perceptions of inequality – the feeling that others around you are getting a better deal. Yet, whereas most of the literature focusing on social status loss has measured this using subjective indicators, this paper measures how actual localized inequality fuels support for the radical right.[1]

How do we measure local inequality using objective, rather than subjective, survey-based data? One very obvious indicator of wealth, and therefore also inequality of wealth, is the value of housing (Ansell et al. 2022; Adler and Ansell 2020). The value of your dwelling compared to other houses in your neighborhood is a clear signal of your relative status. It is obviously distinct from labor market incomes or economic insecurity more generally, but we argue that it captures an important element of relative social status. Even if people are in relatively secure employment with decent wages, they may feel relative social status loss and lack of social recognition if they are surrounded by higher value houses, and thus "higher status" neighbors (Gidron and Hall 2017; Kurer and Gallego 2019). If support for the populist right is driven by relative social status considerations, as we argue, then we would expect it to be higher in local areas with higher levels of inequality in house prices, as more people in such localities would experience relative social status concerns and perceived inequality.

We test this argument by examining the impact of local housing-driven wealth inequality on support for the United Kingdom Independence Party (UKIP) and later Reform UK, the most prominent right-wing populist parties in Britain during the period under investigation. To do this, we construct a novel dataset combining multiple administrative and survey data sources. We first combine the universe of housing transactions registered with the UK Government with detailed energy certificate data on household characteristics for over 26 million residential properties. This rich dataset allows use to apply machine learning methods to predict the dynamic property values for the majority of residential properties in the UK. After extensive

1. There are other recent studies that also use local economic housing data to estimate the effect on populist support. For example, Abou-Chadi, Cohen, and Kurer (2024) use data on local rent levels to demonstrate an effect on support for radical right parties among long-term residents with lower household incomes. In another study, Ansell et al. (2022) use local and individual-level data from Denmark to demonstrate that negative shocks to house prices over the election cycle are strongly associated with support for the populist right. These papers do not, however, explicitly measure the effect of local inequality of populist support.

validation using a separate dataset from Zoopla (Bailey and Georgiou 2025), a house price valuations company covering the UK, we calculate housing wealth inequality using the GINI value annually for each local electoral ward. This allows us to generate a small-area measure of dynamic house price inequality from 1995 to 2022.

We then adopt a number of empirical strategies that allow us to estimate the effects of local inequality on support for populist right parties using voting behavior data and survey data. In order to take advantage of our granular inequality data, we compile a dataset that includes the universe of English local election results between 2006 and 2021, allowing us to systematically analyze the relationship between local-level housing inequality and vote share. In addition to electoral behavior data, we confirm our findings using panel survey data on vote intention from the high-quality Understanding Society Panel (University of Essex, Institute for Social and Economic Research 2023). Across three separate research designs and two different sources of data, the results paint a consistent picture: increasing local inequality drives support for populist right parties. Specifically, our results show that a one-standard deviation increase in house price inequality is followed by a 2-5 percent increase in UKIP/Reform UK vote share and a similar increase in vote intention.

Relative Social Status and Populist Right Support

Political behavior is not only driven by absolute economic fortunes; it is also shaped by how citizens imagine their position relative to others. Classic work on relative deprivation argues that individuals benchmark their standing against proximate reference groups (Runciman 1966; Festinger 1954). As the neighborhood is one of the most proximal settings in people's lives, it is important to understand how an individual's relative social status locally matters for their political attitudes and behaviors. Indeed, empirical studies in social psychology have shown that people's income relative to neighborhood income can matter to mental health and well-being (Roy, Godfrey, and Rarick 2016). This is not surprising since the local area provides a very visible indicator of our standing relative to others. People can form their yardsticks from the immediately visible housing stock, cars on the street, and neighbors' lifestyles. For example, individuals in relatively low-value houses living in high-wealth neighborhoods may perceive their social status as low, regardless of absolute income and wealth. When a visible

gap in wealth emerges between individuals and their neighbors, people may interpret the change as evidence of relative status decline and unfairness – even when their own real income might be flat or even rising.

A long-running debate among scholars of populism has centered on the relative importance of economic and cultural factors in explaining support for the populist right. Cultural explanations contend that a "cultural backlash" among older, white, native-born voters fuels populist-right success as progressive values spread (Norris and Inglehart 2019; Bolet 2021; Margalit, Raviv, and Solodoch 2022). In contrast, several scholars have argued that economic grievances, such as labor market competition and limited economic opportunities, are the primary drivers of support for populist right parties (Colantone and Stanig 2018; Rodrik 2021; Walter 2021). Inherent to both explanations is the idea that voters feel aggrieved by their relative position in society, and that this relative status loss drives support for anti-establishment parties. Status threat, or the anxiety that arises from perceived relative decline, is therefore a key mechanism that links both economic and cultural explanations of populism (Gidron and Hall 2017; Bonikowski 2017; Kurer and Gallego 2019; Kurer 2020).

Shocks that disrupt the local status quo, such as factory closures (Colantone and Stanig 2018; Walter 2021) or influxes of migrants (Bolet 2020), can trigger feelings of relative status loss and therefore increased support for populist right parties. These shocks are often interpreted through the lens of who is advancing and who is being left behind in their immediate surroundings (Gidron and Hall 2017; Bonikowski 2017). Social comparison theory tells us that such proximal cues weigh more heavily than national aggregates (Engler and Weisstanner 2021; Roy, Godfrey, and Rarick 2016).

Housing markets create exactly this kind of visible yardstick (Arzheimer and Bernemann 2024). When a local area experiences a sudden influx of wealth, such as the construction of luxury flats or the arrival of affluent newcomers, it can trigger feelings of relative status loss among existing residents. This is particularly true in areas where housing prices have remained stagnant (Ansell et al. 2022), and where the new developments create a stark contrast to the existing housing stock. The arrival of luxury flats or affluent newcomers can therefore trigger feelings of relative status loss through two mutually reinforcing channels activate. Instrumentally, lower-status voters punish the mainstream parties they deem complicit in skewed development and

reward anti-establishment challengers. Emotionally, status threat sharpens boundary-defense: Gidron and Hall (2017) find that those who feel "looked down upon" express stronger hostility to immigrants and cosmopolitan elites – frames that populist-right entrepreneurs link directly to luxury-led gentrification and "unaffordable housing for locals" (De Vries and Hobolt 2020; Adler and Ansell 2020). Moreover, when public discourse links the perceived loss of status to remote cosmopolitan elites and pliant mainstream parties, the populist right's anti-establishment narrative becomes compelling to those who experience relative status loss locally.

We therefore expect that locally salient increases in visible inequality will heighten subjective status threat, which in turn raises support for right-wing populist parties. In other words, our expectation is that a rise in local inequality – as proxied by house price inequality - will also lead to higher levels of support for the populist radical right. We expect that this effect will be particularly pronounced in areas where new developments create a stark contrast to the existing housing stock, reminding residents of their relative status loss.

Research Design

Our research design exploits small-area estimates of inequality which we derive by first estimating the values of residential houses in the UK and using these estimates to calculate housing price inequality for annually each electoral ward from 1995-2022. After validating the new measure against an existing data source, we estimate the effects of changes in local inequality on support for populist right parties using data from local elections and survey data and using two different research designs. The results provide strong and consistent evidence that increasing local inequality shapes support for populist right parties.

Data

We assemble data from a number of sources. To estimate dynamic housing prices for residential properties in the UK, we link two sources of government administrative data. The first data source is the UK Prices Paid data (UK Government 2024b), which contains every residential property transaction in the UK since 1995. This dataset has the price paid for the property, the transaction date, and the exact location of the property. The second data source comes from the UK Department for Levelling Up, Housing & Communities and contains energy performance

certificates based on energy efficiency inspections (UK Government 2024a). Starting in 2012, every property that was sold or rented required an energy certificate. Additionally, different government programs have incentivized energy inspections and the dataset includes inspections that date back to the 1980s. In total, there are nearly 27 million energy inspections and we are able to match these inspections on the exact address for nearly 11 million residential properties, which amounts to nearly half of all residential properties in England.

Further detailed discussion of the merging and data handling procedures are provided in Appendix A. It is likely that the final dataset under-represents older houses that have not changed hands nor have been rented. The prices paid data contains every transaction since 1995, while the energy certificates data contains every property that has been bought, sold or rented since 2012. Therefore, newer properties and rental properties are more likely to make it into the final dataset. According to the ONS,[2] there were approximately 24.9 million residential properties in England. Our dataset contains 14.1 million unique properties, which amounts to over half of all properties in England. Intuitively, we might expect older properties that have not been sold or rented since before 1995, or inspected at any point, to include higher-value homes that are passed down within families. To the extent that these are higher value homes on average, downstream estimates of inequality based on house prices would be biased downward, shrinking inequality toward zero.

To understand support for populist right parties, we rely on two different datasets. First, we compile a new panel dataset on UK Local Elections at the electoral ward level that spans from 2006 to 2021. The dataset contains the results of every local election at the ward level, which are administrative areas within local councils. There are 8,694 electoral wards, and they contain approximately 5,500 people on average as of 2022. We collect local election results from several sources, included the UK Electoral Commission and UK Local Authorities. We use this data to calculate the vote share for the UK Independence Party (UKIP) in each ward for each election. UKIP is a right-wing populist party that has been a major force in UK politics since the early 2010s. We focus on UKIP because it is a party that has been associated with anti-establishment and anti-immigrant sentiment, and is widely seen as a right-wing populist party (Rooduijn et al. 2024).

In addition to UK local elections data, we use the Understanding Society Panel (University

2. https://www.ons.gov.uk/peoplepopulationandcommunity

of Essex, Institute for Social and Economic Research 2023). We gain access to a restricted version of the dataset that contains individuals' census output areas (2021 Lower Layer Super Output Area (LSOA)). LSOAs are much smaller than electoral wards and typically comprise of between 400 and 1,200 households. The panel contains approximately 30,000 individuals per survey wave, and covers 13 waves from 2008-2023. In our estimations, we focus on a question asking about individuals' vote intention should the next election be held tomorrow.

We additionally collect data from a number of different government sources to use as covariates in our estimations. These include variables such as local economic conditions, local immigration, local demographic characteristics and others. We provide further details and the exact sources for each covariate and its operationalization in Appendix B

Estimating House Prices

We rely on machine learning methods to estimate the value of residential properties in the UK. Namely, we utilize a gradient boosting regression tree model (e.g. `XGBoost`) (Chen and Guestrin 2016) to estimate a function $f : \mathbb{R}^{n \times d} \rightarrow \mathbb{R}^n$ such that $\mathbf{y} = f(\mathbf{X}) + \epsilon$. We estimate this function after optimizing model hyperparameters via 100 trials with an optimization strategy intended to minimize root mean squared error (RMSE). As our dataset is far too large to fit into local memory on a laptop, we train the model on an Amazon EC2 instance with an A100 GPU. We first optimize the model's hyperparameters using 80% of the data and calculate validation metrics for the best model. We then train a final model on the full dataset using the optimal discovered hyperparameters, and then use that model for inferences for dynamic values. The model performs well and is able to predict the value of residential properties to an average accuracy of within about 10% of the true price paid. For example, the model would predict that a given house's value is between £270k and £330k if the true price paid was £300k. Further details of the estimation and analysis are provided in Appendix C.

Measuring Inequality

After training the model, we use it to estimate the value of each residential property available in the dataset between 1995 and 2024. The GINI value is then calculated for a given year and area by using the estimated house prices. The GINI value is a measure of inequality that

ranges from 0 to 1, where 0 indicates perfect equality and 1 indicates perfect inequality. Similar methods to measuring inequality at a local level using housing price data have been employed in previous studies in the UK (Suss 2023) and elsewhere (Domènech-Arumí 2025). The GINI index is calculated as:

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

Where G is estimated housing inequality in electoral ward i at time t. N is the number of observations (e.g., properties in the area), x_i and x_j are the house prices of observations k and j, respectively, and $\bar{x}$ is the mean house price: $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$. The numerator of the GINI index is the sum of the absolute differences between all pairs of house prices, and the denominator is a scaling factor that normalizes the index.

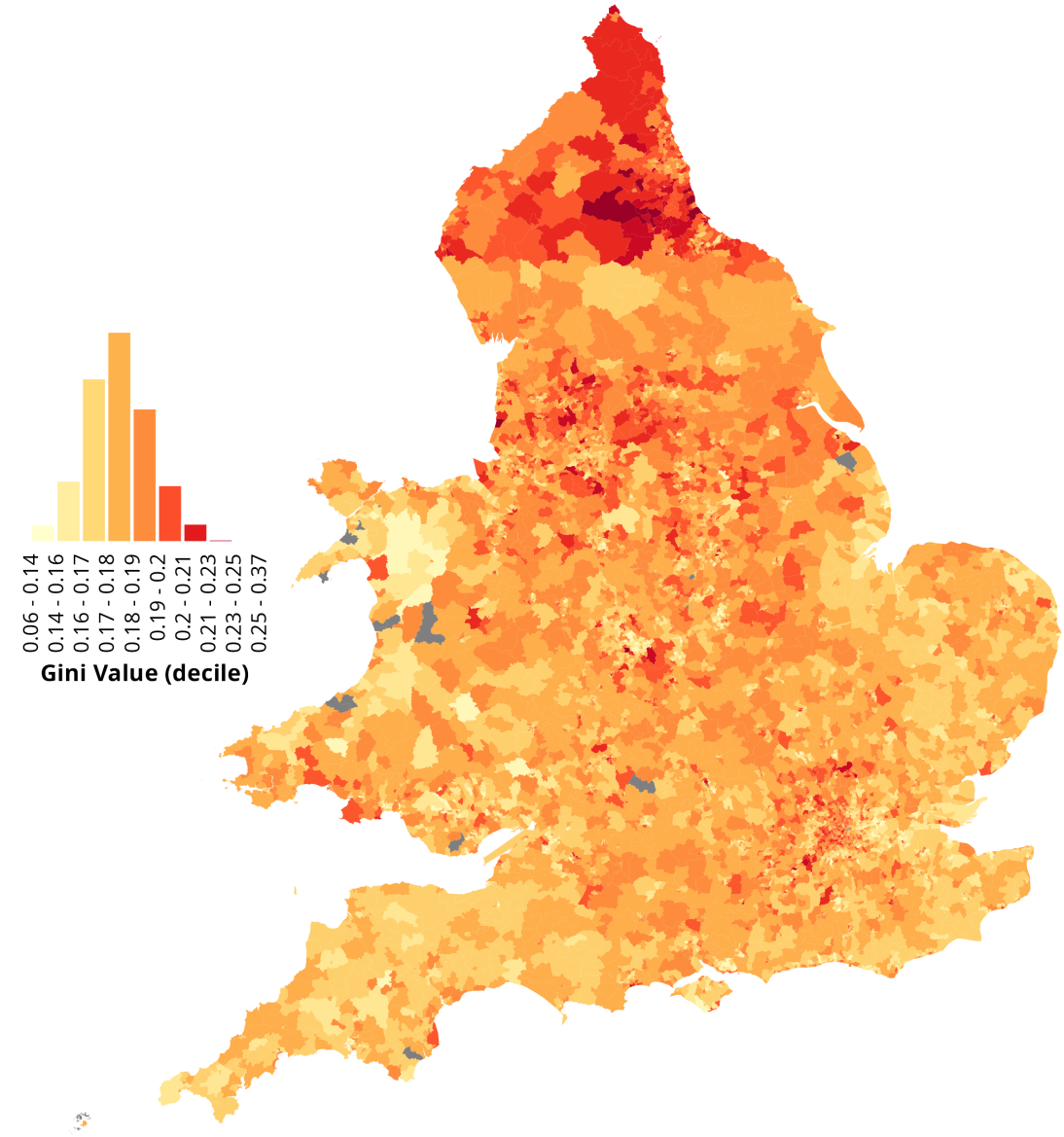
We calculate the GINI value for each electoral ward in the UK for each year between 1995 and 2022. This allows us to examine the spatial and temporal variation in house price inequality across the UK. We show the spatial distribution of house price inequality in the UK in 2022 in Figure 1. The figure suggests considerable variation in the level of house price inequality across the UK, with the highest levels of inequality appearing to occur in northern England.[3]

Measurement Validity

There are few sources of data that provide local level inequality measurements dynamically for the UK. We therefore provide a combination of several "tests" aimed at probing the validity of our measure of inequality. First, we compare our method of measuring inequality with a previous method that uses different data to calculate house prices and GINI values at a different geographic level. Suss (2023) estimates inequality using house price data from Zoopla, a house price valuations company and property data provider. Using nearly 27 million housing value estimates from Zoopla, Suss (2023) calculated the GINI coefficient and average house prices at the Middle Super Output Area (MSOA) level for 2019 (MSOAs are census output areas and

3. Interestingly, the map also shows that house price inequality is not necessarily higher in urban areas, as one might expect. This is consistent with the idea that house price inequality is driven by a combination of factors, including the availability of housing stock, the quality of housing, and the desirability of the area. In Appendix D, we present a similar map of the mean house prices in the UK in 2022, which shows that average house prices are much higher in and around London, and are generally higher in the south of England compared to the north as we might expect.

Figure 1: Spatial Distribution of House Price Inequality in the UK in 2022

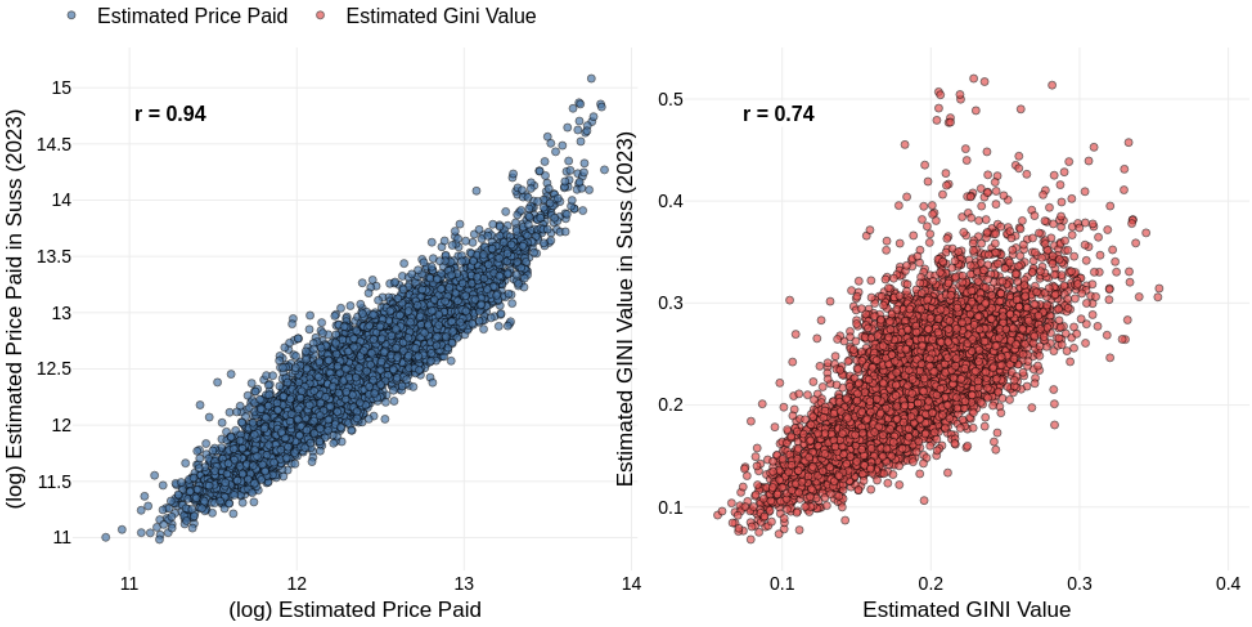


Note: The map shows the GINI values in each electoral ward. The GINI values are cut by deciles, which are labeled in the legend and presented as a histogram to show the distribution of inequality across wards. Darker colors indicate higher levels of inequality. Areas in gray did not meet a minimum threshold of 50 property transactions in a given year.

there are about 8,000 MSOAs in England). To provide a comparison of the author's method and data to our own, we re-estimated the GINI values for each MSOA in the UK using our 2019 data.

Figure 2 suggests a very high correlation in the estimated mean house price and estimated

Figure 2: Comparison to Estimated Price and GINI Value in Suss (2023)



Note: The figure compares estimated price paid and GINI values at the MSOA level using the approach outlined in this article and the approach taken by Suss (2023) using a different source of data.

GINI value using our method and the method used in Suss (2023) that relied on an entirely different dataset. In each subplot, the correlation coefficient is presented in the top-left corner. To the extent that there are differences in predictions of inequality, Suss (2023)'s method appears appears to predict higher levels of inequality as the GINI increases, suggesting that our estimates for inequality may be more conservative in highly unequal areas.

Second – and more substantively important for the analysis – the proposed measurement of inequality needs to capture the perceptions of voters that their local areas are indeed unequal. For this, we turned to survey data from wave 3 of the British Election Study (BES) (Fieldhouse et al. 2023). Wave 3 of the BES was fielded in September and October of 2014, and is the only wave in which respondents were asked about inequality in their local community. Specifically, respondents were asked "How large are the differences in income in your local community? Please give your best guess by choosing a point on the following scale." In total, there are responses and geographic identifiers for 10,019 respondents who answered the question on a 7-point scale. Using census MSOA identifiers for these respondents, we estimated a series of regressions relying on spatial variation to understand the degree to which

inequality as measured by our estimates predicts perceptions of inequality as measured by the survey data. Across several models using various configurations of individual and local area control variables, the association between our objective measure of inequality and individuals' perceptions of inequality is strong and meets conventional levels of statistical significance. In the most conservative model which includes demographic and socioeconomic characteristics, as well as local area characteristics such as unemployment, deprivation and immigration, a one-standard deviation increase in GINI value amounts to a 0.05 point increase in perceived inequality (measured on a seven-point scale).[4] We take this as strong evidence that individuals accurately perceive the level of inequality in their local communities.

Empirical Strategies

Identifying the causal effect of inequality poses numerous challenges. We therefore adopt multiple empirical strategies using different sources of data to estimate the relationship between inequality and local support for populist right parties. The first strategy is a selection-on-observables design with two-way fixed effects regressions that include a wide array of relevant control variables. This strategy ensures that estimates are derived only from changes within individual units over time. We use this strategy on both datasets. This means that estimates are derived using changes within local wards that for the local elections dataset. For the Understanding Society Panel, estimates are derived only from changes within individuals. These approaches are likely the most conservative and control for time-invariant heterogeneity between units as well as time-variant shocks that affect all units. We estimate the following model using ordinary least squares (OLS) regression:

$$\mathrm{Y}_{i,t} = \alpha_i + \gamma_t + \delta \mathrm{Inequality}_{it-1} + X_{i,t-1} + \epsilon_{i,t} \tag{2}$$

Where Y is UKIP vote share in ward i in year t, Inequality is the GINI value in ward i in year $t-1$, and X_{it-1} is a vector of control variables listed above. We include ward fixed effects α_i and year fixed effects γ_t to account for time-invariant differences between wards and time-variant shocks that affect all wards, respectively. The coefficient of interest is δ, which captures the relationship between changes in inequality and UKIP vote share. The error term

4. Full results are presented in Appendix E.

is denoted by ϵ_{it}.[5]

In a second strategy, we use variation in inequality driven by new, high-value housing developments to identify the effects of inequality on support for populist right parties. Using the housing prices paid data (UK Government 2024b), we identify new housing developments that far exceed the average housing value for a given area in a given year. This process follows several steps. First, the mean and standard deviation for newly built houses in each local electoral ward and each year is calculated. We then identify cases in which a newly-built property is two standard deviations above the mean price paid for a new property in the same area in the same year. This corresponds to a new house that is in the $\sim$ 98th percentile (or higher) compared to the prices paid for new houses in that local area in the same year.

The idea behind this strategy is that the new, high-value residential property increases inequality by definition, and therefore lends itself to a natural experiment in which this increase in inequality can be used as an instrument to estimate the effects of inequality on electoral support for populist right parties. We choose to use only properties that are 2 standard deviations above the mean instead of below to allow for the possibility that an area is improving rather than declining given the associating between deprivation and support for the populist right (Burgoon et al. 2019; Ferwerda, Gest, and Reny 2024).

This strategy further allows for understanding the duration of the effects of a spike in inequality by estimating an event study model. Given the staggered nature of new high-value houses being built, we estimate a reduced form model that captures the dynamic effects of the new, high-value properties on vote intention for a populist right party for individuals who are exposed. Our event study model which we estimate using the estimator developed in Sun and Abraham (2021) can be formalized as follows:

$$Y_{i,t} = \alpha_g + \lambda_t + \sum_{\ell \neq -1} \mu_\ell 1\{t - E_i = \ell\} + X'_{i,t} + \varepsilon_{i,t} \tag{3}$$

Where $Y_{i,t}$ is vote intention for a populist right party for individual i at time t. E_i represents the time of exposure to a new high-value property. The coefficients μ_ℓ estimate the effect of

5. We standardize the GINI values to make the results substantively interpretable. Many control variables are measured at the local authority level annually. Exceptions are ethnic composition and education, both of which are measured by the UK Census in 2001, 2011 and 2021 at the electoral ward level and are then interpolated linearly. Results are not sensitive to dropping these interpolated variables, but we present all results with and without these variables.

exposure at each relative time period ℓ, with the pre-treatment period immediately prior to exposure ($\ell = -1$) serving as the baseline category. X_{it} is a vector of time-variant control variables measured annually at the local level, including the unemployment rate, material deprivation, international immigration and others listed below. Fixed effects for individual areas (α_g) and time periods (λ_t) are included to control for time-invariant differences between areas and time periods. The error term $\varepsilon_{i,t}$ captures idiosyncratic variation in support for a populist right party.

The specification enables us to assess the plausibility of the parallel trends assumption (at least during the pre-treatment period) through the coefficients for $\ell < -1$ and to estimate the average effects of new, high-value properties on vote intension for a populist right party in each relative period ($\ell \geq 0$).

The Electoral Effects of Inequality

We first present the results of the two-way fixed effects regressions using the first empirical strategy described above with the local election panel dataset. The results are presented in Table 1 with different combinations of the control variables. In all estimations, the GINI value is standardized to provide interpretable estimates. We can therefore understand the coefficient estimates in terms of a one-standard-deviation change in inequality. For example, a standardized GINI estimate of 0.03 suggests that a one-standard-deviation increase in inequality is followed by a 3-percent-point increase in UKIP/Reform UK vote share.

Across each of the specifications, the effects of changes in inequality on UKIP/Reform UK vote share are positive and significant. In the most conservative model which includes all available control variables, the estimates suggest that a 1-standard deviation increase in inequality amounts to an increase of 2 percentage points for UKIP/Reform UK.

High Value Properties as a Natural Experiment

The results presented in Table 1 and in Appendix I (Table A6 and Table A5) suggest a statistically significant relationship between local inequality and support for populist right parties. The estimates across multiple models and when using two different sources of data tell a consistent story. Yet, making inferences about the effects of inequality without exogenous variation

Table 1: Effects of Changes in Inequality on Support for UKIP/Reform Vote Share

	UKIP/Reform Vote Share			
	(1)	(2)	(3)	(4)
GINI (standardized)	0.027***	0.027***	0.025***	0.020***
	(0.004)	(0.005)	(0.005)	(0.005)
Economic & Immigration controls		✓	✓	✓
Economic, Immigration & Education controls			✓	✓
All controls				✓
Num.Obs.	13065	10525	10525	10310
R2	0.771	0.791	0.792	0.812
Electoral Ward fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓

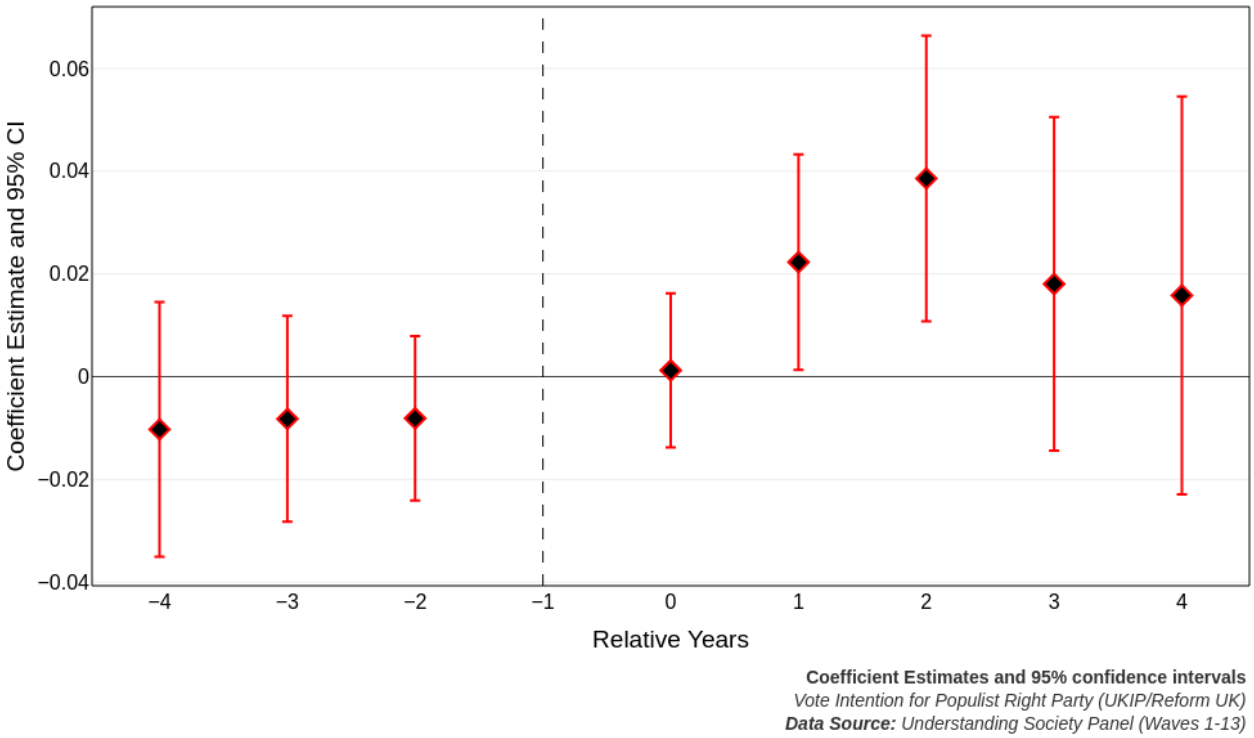
Note: All models include fixed effects for electoral ward and year and clustered standard errors by ward. Model 1 does not include controls. Model 2 includes economic and immigration controls. Model 3 include economic, immigration and education controls. Model 4 includes economic, immigration, education, demographic and deprivation controls. Economic controls include unemployment claims, GDP per capita, and gross disposable income. Immigration controls include international immigration, domestic migration, and GP practice registrations by migrants. Education controls include the share of levels 1, 2, 3 and no qualifications, respectively, for each ward. Model 4 with all available controls additionally includes ethnic composition (Black, white, Asian), ward population, mean house value, and Index of Multiple Deprivation. The full results, including each control variable included in the respective models, are presented in Appendix F.

raises challenges. We therefore rely on the second empirical strategy articulated in previous sections that makes use of new, high-value properties which, by definition, raise the level of inequality in a given area. The results of the event study formalized in Equation 3 are presented in Figure 3.

Figure 3 suggests that in the years prior to a new, high-value property, there are non-significant differences in vote intention for populist right parties. However, following a new, high-value property which increases the level of inequality in a local area, support for Reform UK/UKIP increases by an average of about two percentage points in year one and as much as four percentage points in year two. The effects appear to revert to mean levels by year three. Taken in combination with the two-way fixed effects regressions presented previously, the dynamic results suggest that rising inequality shapes support for populist right parties, with local residents who live in much lower priced homes responding to new residents in their local areas in higher value homes.[6]

6. We provide the full results of this analysis in table format in Appendix J.

Figure 3: Dynamic Effects of Inequality on Support for Populist Right Party



Note: The figure provides reduced form event study estimates for the dynamic effects of a high-value new property on support for a populist right party. The estimates presented above do not include any control variables. Results with various configurations of the control variables are available in Appendix J.

Robustness Checks

Shift-share Instrumental Variable Design

Despite the inclusion of a wide range of control variables, there may still be concerns about omitted variable bias, or that there is another factor that might be driving the results we observe. We adopt a shift-share instrumental variables strategy to add robustness to the findings that inequality drives support for UKIP/Reform UK (Borusyak, Hull, and Jaravel 2024). In this design, which is explained in detail in Appendix G, we instrument inequality using the Right-to-buy program which allowed individuals to purchase their council homes. The results suggest similar and statistically significant results as the two-way fixed effects regressions. Specifically, a 1-standard deviation increase in inequality is followed by a 4-6 percent increase in vote share for a populist right party.

Evidence from Survey Data

Despite strong evidence of the association between inequality and support for the populist right using electoral data, we additional probe the robustness of our main results using survey data. Specifically, we replicate the results of the main analysis estimating changes in levels of inequality on support for populist right parties using vote intention measured using individual survey data. For this analysis, we use the Understanding Society Panel (University of Essex, Institute for Social and Economic Research 2023), which includes approximately 30,000 households per year from 2009 to 2024. The benefit of these data are that they allow us to control for individual characteristics such as monthly income, education and job status, which may drive support for populist parties. Using the entire panel and two-way fixed effects regressions formalized in Equation 2, the estimated results which are presented in Table A6 are nearly identical to the local election results. Namely, a one-standard deviation increase in inequality is followed by a 2-3 percentage point increase in voting for UKIP and Reform UK. The full results are presented in Appendix I.

Conclusion

The results presented in this paper provide strong and consistent evidence that increases in local inequality shapes support for populist right parties. Using a new measure of local inequality based on machine learning estimates of housing prices, we find that increases in local inequality are associated with increased support for UKIP/Reform UK in local elections and in survey data. The results are robust to a wide range of control variables and alternative specifications, including an event study design that exploits the arrival of new, high-value properties as a natural experiment.

The findings suggest that rising local inequality, particularly in the form of new, high-value housing developments, can drive support for populist right parties, likely as rising relative inequality triggers feelings of relative status loss among citizens of declining status. We know that radical right populist parties tend to capitalize on these sentiments by framing themselves as defenders of "ordinary people" against perceived threats from elites and newcomers (Mudde 2007).

Although our findings are based on the UK context, they have broader implications for understanding the ways in which relative status threat may contribute to support for populism in other countries. While aggregate level inequality, or even individual-level deprivation, have not always be good predictors of radical right support, our results expand the growing literature showing that relative status loss is an important factor. The robust association between local inequality and support for populist right parties demonstrated in this paper may be relevant in other contexts as well. Future research could explore these dynamics in different countries and regions, as well as as further investigate the mechanisms linking local inequality and support for the radical right.

References

Abou-Chadi, Tarik, Denis Cohen, and Thomas Kurer. 2024. "Rental Market Risk and Radical Right Support." *Comparative Political Studies.*

Adler, David, and Ben Ansell. 2020. "Housing and populism." *West European Politics* 43 (2): 344–365.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2021. "Individual vulnerability to industrial robot adoption increases support for the radical right." *Proceedings of the National Academy of Sciences* 118 (47): e2111611118.

Ansell, Ben, Frederik Hjorth, Jacob Nyrup, and Martin Vinæs Larsen. 2022. "Sheltering populists? House prices and the support for populist parties." *The Journal of Politics* 84 (3): 1420–1436.

Arzheimer, Kai, and Theresa Bernemann. 2024. "'Place'does matter for populist radical right sentiment, but how? Evidence from Germany." *European Political Science Review* 16 (2): 167–186.

Bailey, Nick, and Michail Georgiou. 2025. "Zoopla Property Listings Gen1."

Bartik, Timothy J. 1991. "Who Benefits from State and Local Economic Development Policies?" *WE Upjohn Institute for Employment Research.*

Bekhtiar, Karim. 2025. "The decline of manufacturing employment and the rise of the far-right in Austria." *Journal of Public Economics,* 105315.

Bolet, Diane. 2020. "Local Labour Market Competition and Radical Right Voting: Evidence from France." *European Journal of Political Research* 59 (4): 817–841.

———. 2021. "Drinking Alone: Local Socio-Cultural Degradation and Radical Right Support—the Case of British Pub Closures." *Comparative Political Studies* 54 (9): 1653–92.

Bonikowski, Bart. 2017. "Ethno-Nationalist Populism and the Mobilization of Collective Resentment." *The British Journal of Sociology* 68:S181–S213.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of economic studies* 89 (1): 181–213.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2024. *A practical guide to shift-share instruments.* Technical report. National Bureau of Economic Research.

Burgoon, Brian, Sam Van Noort, Matthijs Rooduijn, and Geoffrey Underhill. 2019. "Positional deprivation and support for radical right and radical left parties." *Economic Policy* 34 (97): 49–93.

Chen, Tianqi, and Carlos Guestrin. 2016. "Xgboost: A scalable tree boosting system." In *Proceedings of the 22nd ACM sigkdd international conference on knowledge discovery and data mining,* 785–794.

Ciccolini, Giuseppe. 2021. "Left Behind Whom? Economic Status Loss and Populist Radical Right Voting."

Colantone, Italo, and Piero Stanig. 2018. "The trade origins of economic nationalism: Import competition and voting behavior in Western Europe." *American Journal of Political Science* 62 (4): 936–953.

———. 2019. "The Surge of Economic Nationalism in Western Europe." *Journal of Economic Perspectives* 33 (4): 128–51.

Cramer, Katherine J. 2016. *The Politics of Resentment: Rural Consciousness in Wisconsin and the Rise of Scott Walker.* University of Chicago Press.

De Vries, Catherine, and Sara Hobolt. 2020. *Political entrepreneurs: The rise of challenger parties in Europe.* Princeton University Press.

Domènech-Arumí, Gerard. 2025. "Neighborhoods, perceived inequality, and preferences for redistribution: Evidence from Barcelona." *Journal of Public Economics* 242:105288.

Engler, Sarah, and David Weisstanner. 2021. "The threat of social decline: income inequality and radical right support." *Journal of European Public Policy* 28 (2): 153–173.

Ferwerda, Jeremy, Justin Gest, and Tyler Reny. 2024. "Nostalgic deprivation and populism: Evidence from 19 European countries." *European Journal of Political Research.*

Festinger, Leon. 1954. "A theory of social comparison processes." *Human relations* 7 (2): 117–140.

Fieldhouse, Ed, Jane Green, Geoffrey Evans, Hermann Schmitt, Cees van der Eijk, Jon Mellon, and Chris Prosser. 2023. *British Election Study.*

Gidron, Noam, and Peter A Hall. 2017. "The Politics of Social Status: Economic and Cultural Roots of the Populist Right." *The British Journal of Sociology* 68:S57–S84.

Gidron, Noam, and Jonathan JB Mijs. 2019. "Do changes in material circumstances drive support for populist radical parties? Panel data evidence from The Netherlands during the Great Recession, 2007–2015." *European Sociological Review* 35 (5): 637–650.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review* 110 (8): 2586–2624.

Guiso, Luigi, Helios Herrera, Massimo Morelli, and Tommaso Sonno. 2024. "Economic insecurity and the demand for populism in Europe." *Economica* 91 (362): 588–620.

Hobolt, Sara B. 2016. "The Brexit vote: a divided nation, a divided continent." *Journal of European Public Policy* 23 (9): 1259–1277.

Kurer, Thomas. 2020. "The declining middle: Occupational change, social status, and the populist right." *Comparative Political Studies* 53 (10-11): 1798–1835.

Kurer, Thomas, and Aina Gallego. 2019. "Distributional Consequences of Technological Change: Worker-Level Evidence." *Research & Politics* 6 (1).

Margalit, Yotam. 2019. "Economic insecurity and the causes of populism, reconsidered." *Journal of Economic Perspectives* 33 (4): 152–170.

Margalit, Yotam, Shir Raviv, and Omer Solodoch. 2022. "The Cultural Origins of Populism." *Available at SSRN 4001543.*

Mudde, Cas. 2007. *Populist Radical Right Parties in Europe.* Cambridge: Cambridge University Press.

Norris, Pippa, and Ronald Inglehart. 2019. *Cultural backlash: Trump, Brexit, and authoritarian populism.* Cambridge University Press.

Rodrik, Dani. 2021. "Why does globalization fuel populism? Economics, culture, and the rise of right-wing populism." *Annual Review of Economics* 13:133–170.

Rooduijn, Matthijs, Andrea LP Pirro, Daphne Halikiopoulou, Caterina Froio, Stijn Van Kessel, Sarah L De Lange, Cas Mudde, and Paul Taggart. 2024. "The PopuList: A database of populist, far-left, and far-right parties using expert-informed qualitative comparative classification (EiQCC)." *British Journal of Political Science* 54 (3): 969–978.

Roy, Amanda L, Erin B Godfrey, and Jason RD Rarick. 2016. "Do we know where we stand? Neighborhood relative income, subjective social status, and health." *American journal of community psychology* 57 (3-4): 448–458.

Runciman, Walter Garrison. 1966. "Relative deprivation and social justice: A study of attitudes to social inequality in twentieth-century England." *(No Title).*

Scheiring, Gábor, Manuel Serrano-Alarcón, Alexandru Moise, Courtney McNamara, and David Stuckler. 2024. "The Populist Backlash Against Globalization: A Meta-Analysis of the Causal Evidence." *British Journal of Political Science,* 1–25.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2): 175–199.

Suss, Joel H. 2023. "Measuring local, salient economic inequality in the UK." *Environment and Planning A: Economy and Space* 55 (7): 1714–1737.

UK Government. 2024a. *Energy Performance of Buildings Data.*

———. 2024b. *Prices Paid Data.*

University of Essex, Institute for Social and Economic Research. 2023. "Understanding Society: Waves 1–13, 2009–2022 and Harmonised BHPS: Waves 1–18, 1991–2009." *UK Data Service.*

Walter, Stefanie. 2021. "The Backlash Against Globalization." *Annual Review of Political Science* 24 (1): 421–442.

Part I
Appendix

Table of Contents

A Data Assembling and Merging

We assemble data from a number of sources. To estimate dynamic housing prices for residential properties in the UK, we combine data on the prices paid in every transaction from 1995 (UK Government 2024b) and data on the energy performance of UK residential properties, as reported via Energy Performance Certificates (EPC) (UK Government 2024a).[7] Importantly, we take every available observation in the Energy Performance Certificate data and merge in the prices paid data. The benefit of starting with the EPC dataset is that it contains residential energy inspections that have been recorded since 1980, along with detailed property characteristics, such as the number of rooms, size, age of property, and over 100 other characteristics that we use downstream in our machine learning model to predict house prices. Starting in 2012, all new properties and properties that have been sold or rented require an EPC, which has led to a comprehensive dataset that includes more than 26 million inspections. We merge this dataset with UK Prices Paid data which contains every residential housing transaction since 1995 (UK Government 2024b).[8] The Prices Paid data includes the price paid for each property, the date of the transaction, and the address of the property. We use the address, street name, postcode and county to merge the EPC data with the Prices Paid data.[9] The outcome of this effort is a dataset that contains $\sim$ 25 million transactions between 1995 and 2024 for $\sim$ 11 million different residential properties with detailed characteristics about the properties that varies over time, given that the EPC data is updated every time a new inspection is conducted.

There are several advantages of creating the dataset in the aforementioned order (instead of the reverse). First, we allow for the estimation of house prices for properties that have not been sold since the Prices Paid data started being collected in 1995, but for which an Energy Performance Certificate exists. This makes our sample more representative of the UK residential housing stock, as many properties may not have been sold since 1995. Second, we allow for the possibility that properties are renovated or improved over time, which would be captured in the EPC data in the case that there are multiple inspections for the same property. We can therefore estimate the value of properties at different points in time as they change and prices in their area change.

7. Department for Levelling Up, Housing & Communities: https://epc.opendatacommunities.org/
8. https://www.gov.uk/government/statistical-data-sets/price-paid-data-downloads
9. Details on the merging process are provided in Appendix A.

B Data sources and variable operationalization

There are several sources of data that are used throughout the analysis that require greater detail than the main text allows. Below, discussion of each of the variables and their calculation is included.

(log) Unemployment Rate: Measured annually at local authority level and available from (ONS)

(log) Gross disposable household income: Measured annually at local authority level and available from ONS ONS.

(log) Unemployment Claimant Count: Measured annually at local authority level and available from ONS.

(log) Gross domestic product per head at current market prices: Measured annually at local authority level and available from ONS.

Domestic and international immigration: Measured annually at local authority level and available from ONS. This variable was measured as the number of migrants/domestic immigrants as a proportion of the population in a given area.

Indices of Multiple Deprivation: Measured in 2010, 2015, and 2019 at the lower census output level. The variable is imputed to cover missing years and is aggregated up to the electoral ward level using 2022 ward boundaries. All data available here.

Ethnic composition: Measured in the 2001, 2011 and 2021 censuses at the lower census output level (LSOA). The data were imputed at the LSOA level and then aggregated to the 2022 ward boundaries. Data are available from Nomis, which is the official census and labor market statistics provided for the UK Government.

Education composition: measured using the 2001, 2011 and 2021 censuses. Data were available by electoral ward and were linearly imputed for the missing years. Data available for download from Nomis, which is the official census and labor market statistics provided for the UK Government.

C House Price Estimation

House prices are estimated using a machine learning model that predicts the price of a property based on its characteristics and location. The model is trained on the merged dataset of Prices Paid and Energy Performance Certificate data. There are 11 million matches that come from these two datasets, which contain detailed information about the properties, such as the number of rooms, size, age of property, and over 100 other characteristics.

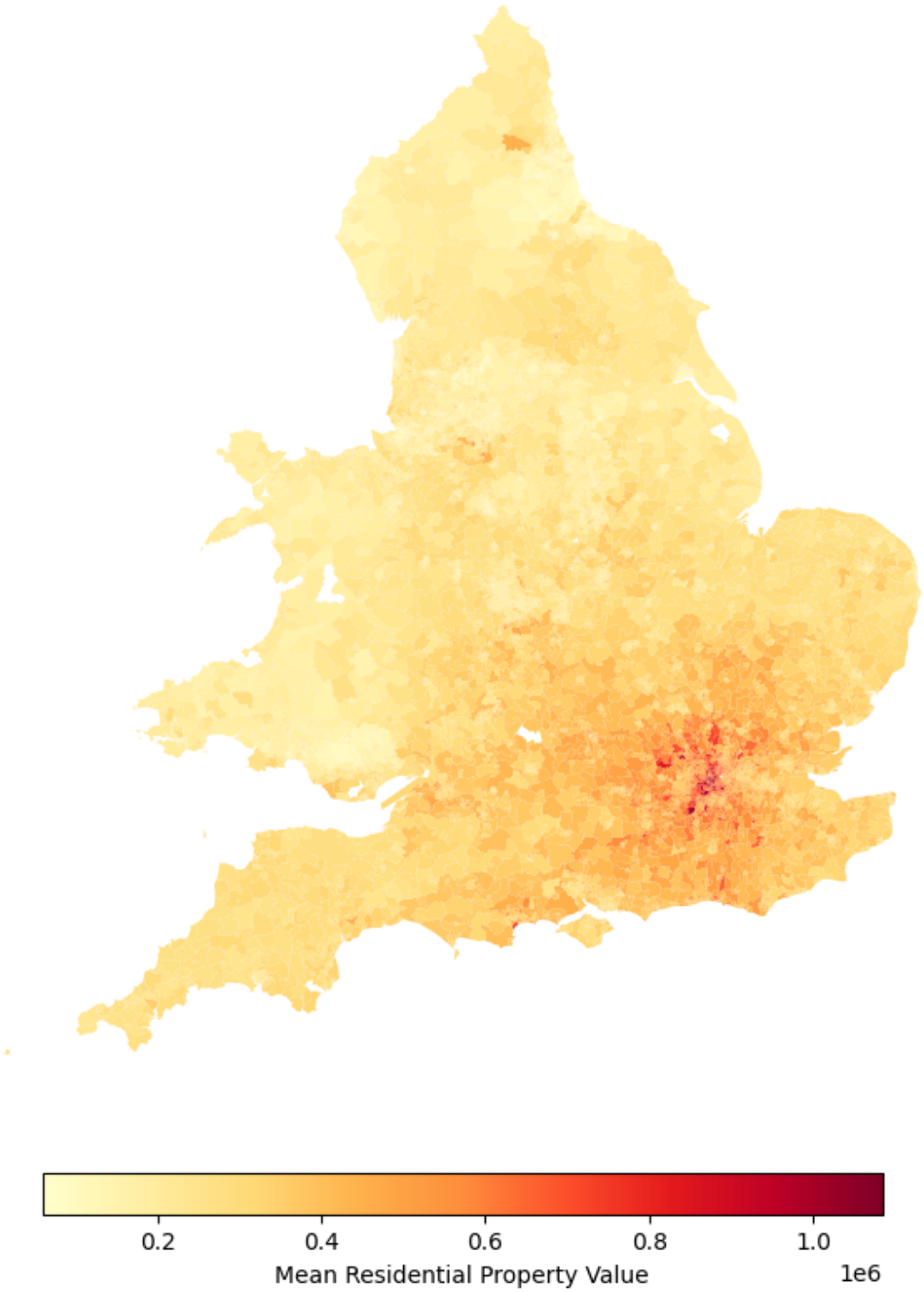
We use the `XGBoost` algorithm (Chen and Guestrin 2016) to estimate the house prices. XGBoost is a gradient boosting algorithm that is widely used for regression and classification tasks. It is particularly well-suited for large datasets and can handle missing values, which is important given that the dataset contains properties with missing characteristics. The model is trained to predict the log price of a property based on its characteristics and location.

The model is first optimized using a random sample of 3 million of these properties until the optimal hyperparameters are found. The model is then trained using the optimal hyperparameters on the remaining 8 million properties. After training the model, we use it to predict the log price of each unique property annually from 1995 to 2024, taking into account whether a given property was purchased new or not. For example, if a property was purchased new in 2000, then we would not predict backwards to 1995, but rather only predict the price of the property from 2000 onwards.

After the model is trained, we treat the prediction task as an imputation task in which create a new dataset that contains the cartesian product of the properties and years from 1995 to 2024. We then use the trained model to predict the log price of each property in each year. The predicted log prices are then exponentiated to obtain the predicted prices in pounds sterling.

D Average House Prices in 2022

Figure A1: Spatial Distribution of House Price Inequality in the UK in 2022



Note: The map shows the average house values of residential properties in 2022.

E Comparison of Measured Inequality with Perceived Inequality

Table A1 present regression results where we regress perceived inequality measuring using wave 3 of the British Election Study on measured inequality from our estimates.

Table A1: Association between Measured Inequality and Perceived Inequality

	Model 1	Model 2	Model 3	Model 4
Gini Value	1.56***	1.38***	1.09**	1.19*
	(0.33)	(0.38)	(0.41)	(0.47)
Household Income		0.00		-0.01
		(0.01)		(0.01)
Homeownership		0.01		0.00
		(0.01)		(0.01)
Social Grade		-0.04***		-0.03*
		(0.01)		(0.01)
Mean Disposable Income			0.29*	0.32+
			(0.14)	(0.17)
Mean Unemployment			-0.12	-0.08
			(0.08)	(0.09)
IMD Score			0.00	0.00
			(0.00)	(0.00)
Immigration			5.89*	7.40*
			(2.51)	(2.92)
Ethnicity		0.01*		0.00
		(0.01)		(0.01)
Mean House Price			0.00**	0.00+
			(0.00)	(0.00)
Num.Obs.	10019	7744	7317	5645
R2	0.002	0.004	0.021	0.021
R2 Adj.	0.002	0.004	0.020	0.019
AIC	35296.0	27340.7	25614.3	19820.8
BIC	35317.7	27389.4	25669.5	19900.4
Log.Lik.	-17645.017	-13663.345	-12799.141	-9898.384
RMSE	1.41	1.41	1.39	1.40
Std.Errors	HC3	HC3	HC3	HC3

F Full Results from UK Local Elections

Table A2 presents the full results from the main text (Table 1). The results are from two-way fixed effects regressions using vote share from local elections.

Table A2: Estimated Effect of Inequality on Support for UKIP Vote Share

	UKIP vote share			
	(1)	(2)	(3)	(4)
GINI (normalized)	0.028***	0.027***	0.025***	0.020***
	(0.004)	(0.005)	(0.005)	(0.005)
Unemployment claims		0.013	0.018	0.029**
		(0.013)	(0.013)	(0.013)
GDP per head		-0.037*	-0.037*	-0.045**
		(0.021)	(0.021)	(0.021)
Gross disposable income		-0.121**	-0.096*	-0.130**
		(0.049)	(0.052)	(0.053)
Immigration		0.360	0.237	1.05
		(1.13)	(1.11)	(1.07)
Migrant GP registrations		1.49*	1.42*	0.781
		(0.764)	(0.773)	(0.712)
White proportion			-0.550**	-0.782***
			(0.224)	(0.218)
Black proportion			-1.57***	-1.84***
			(0.355)	(0.347)
Asian proportion			-0.497**	-0.721***
			(0.238)	(0.233)
Domestic Migration			0.853**	0.798**
			(0.352)	(0.358)
Proportion with GCSE			-9.19×10^{-6}	4.03×10^{-6}
			(2.49×10^{-5})	(2.47×10^{-5})
Proportion with A-Level			4.97×10^{-6}	-6.19×10^{-6}
			(1.18×10^{-5})	(1.25×10^{-5})
No Education Qual.			-0.127	-0.111
			(0.150)	(0.143)
Avg. house price				-0.013
				(0.027)
Ward population				-0.014***
				(0.004)
Total votes				$-8.2 \times 10^{-6***}$
				(6.97×10^{-7})
IMD score				-0.003**
				(0.001)
Electoral Ward fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Observations	13,065	10,525	10,525	10,310
R^2	0.77067	0.79092	0.79239	0.81216
Within R^2	0.00748	0.01030	0.01727	0.08061

G Shift-share IV

Despite the inclusion of a wide range of control variables, there may still be concerns about omitted variable bias. Moreover, it is possible that unobserved factors that affect both house price inequality and UKIP vote share are driving the results, leading to biased estimates in our fixed effects regression. To address this concern, we adopt an shift-share instrumental variable approach that leverages variation from the Right-to-Buy (RTB) program. Shift-share instruments have been used in the literature to estimate the effects of national shifts that have differential effects on local shares, and have been shown to be valid under a range of conditions (Borusyak, Hull, and Jaravel 2022, 2024). For example, Bekhtiar (2025) estimates the causal effects of manufacturing decline on support for the far-right Austrian Freedom Party by instrumenting local manufacturing decline with a shift-share instrument that uses the product of national manufacturing decline and local manufacturing shares. Causal identification with shift-share instruments follows the logic that "a share-weighted average of random shifts is itself as-good-as-random [...] even if the shares are econometrically endogenous" (Borusyak, Hull, and Jaravel 2024, p.6). Applying this logic to the current study, our shift-share instrument captures a housing share-weighted average of the national shift in right-to-buy annual sales in England.[10]

The RTB program was a policy introduced in 1980 under the Thatcher government that allowed council tenants to purchase their homes at a discount. Important for the plausibility of our strategy, the policy reduced inequality (see first stage estimates in **??**) by creating a pathway for lower income individuals to buy their council homes. Moreover, the policy did not require that beneficiaries relocate to a new location, which means that the general composition of local areas was retained. There were additional stipulations that required beneficiaries to live in the property for a certain number of years before selling, which further reduces the likelihood that the policy led to changes in the composition of local areas.

Drawing from the literature on shift-share, or Bartik-style, instrumental variables (Bartik 1991; Borusyak, Hull, and Jaravel 2024; Goldsmith-Pinkham, Sorkin, and Swift 2020), we use the product of national-level shifts in annual Right-to-buy sales and the initial shares of local

10. Data on historical right-to-buy sales are available from the UK Ministry of Housing, Communities and Local Government (https://www.gov.uk/government/statistical-data-sets/local-authority-housing-statistics-open-data).

authority-owned housing stock in 1980 at the start of the policy as a shift-share instrument. We additionally lag the variable by five years to reduce the likelihood that shifts result in other changes that might affect vote behavior. The instrument captures plausibly exogenous variation in inequality by relying on the ways in which the national shock due to the policy change differentially affected local areas according to the proportion of available housing shock before the policy was implemented in 1980.

Our shift-share instrument takes the following form:

$$Z_{it} = NationalShiftRTB_{t-5} \times LocalHousingShare_{i,1980}$$

Where Z_{it} is the shift-share instrument for wealth inequality in local authority i at time t, $NationalShiftRTB$ is the national annual shift in RTB sales at time $t-5$. $LocalHousingShare_i$ is the share of social housing owned by local authority i in 1980 before the start of the policy.

After constructing the instrument, we estimate the following two-stage least squares (2SLS) model, where the first stage predicts house price inequality using the shift-share instrument, and the second stage predicts UKIP vote share using the predicted values of house price inequality. The first and second stages of the model are as follows:

$$GINI_{it} = \alpha_i + \gamma_t + \pi Z_{it} + \epsilon_{it} \tag{4}$$

$$UKIP_{it} = \alpha_i + \gamma_t + \delta \hat{GINI}_{it} + X_{it-1} + \epsilon_{it} \tag{5}$$

Where $\hat{GINI}_{it}$ is the predicted value of the GINI index of house prices in ward i in year t, and Z_{it} is the instrument for house price inequality. The model includes ward fixed effects α_i and year fixed effects γ_t. The error term is denoted by ϵ_{it}. We include in the second stage the same control variables as the fixed-effects regressions, although we present results with and without these variables and they are qualitatively unchanged.

There are two necessary assumptions that must be met for our shift-share instrument to identify the causal effects of inequality on vote share. First, the instrument must be relevant. Namely, it must be correlated with inequality. Our instrument satisfies the relevance condition because areas with a larger share of council houses in 1980 were disproportionately affected by national RTB shifts, leading to greater changes in wealth inequality over time, weighted by

the local shares of social housing stock. We can additionally provide empirical evidence of the correlation between the instrument and inequality via the F-statistic in the first stage of the two-stage regression. The F-statistic is much greater than the conventional minimum of 10, indicating a strong first stage (see Appendix H).

Second, the instrument must affect the outcome – UKIP vote share – *only* through its effect on inequality (e.g. the exclusion restriction). This assumption is fundamentally untestable, but there is evidence to suggest that it may be credible. As mentioned previously, we lag the shift-share instrument by five years to reduce the likelihood that changes in its take-up influence voters through an unobserved mechanism. Additionally, we estimate reduced form specifications in which we regress UKIP vote share on the shift-share instrument while including the control variables *and* measured inequality. The logic here is that if the instrument affected UKIP vote share through a pathway other than the characteristics we observe and include in the model, then the instrument should produce a discernible effect on vote share. We show that this is not the case and that the statistical relationship between the instrument and UKIP vote share when including the other control variables in the model is effectively zero. In fact, even in reduced form regressions without any other control variables but measured inequality produce an estimate that is statistically indistinguishable from zero. We present the results of this analysis in Appendix H.

G.1 First Stage IV Estimates

Table A3: First and Second Stage IV Estimates

IV stages	GINI First (1)	UKIP Second (2)	GINI First (3)	UKIP Second (4)	GINI First (5)	UKIP Second (6)	GINI First (7)	UKIP Second (8)
RTB Shift-share IV	-0.085***		-0.097***		-0.101***		-0.100***	
	(0.009)		(0.015)		(0.014)		(0.015)	
GINI (normalised)		0.065***		0.057***		0.053***		0.047**
		(0.015)		(0.019)		(0.019)		(0.019)
Unemployment claims			0.257***	0.007	0.235***	0.012	0.235***	0.013
			(0.044)	(0.014)	(0.045)	(0.014)	(0.045)	(0.014)
GDP per head			0.280***	-0.051**	0.278***	-0.051**	0.273***	-0.051**
			(0.071)	(0.022)	(0.070)	(0.022)	(0.070)	(0.022)
Gross disposable income			-1.94***	-0.043	-1.69***	-0.034	-1.71***	-0.054
			(0.207)	(0.072)	(0.205)	(0.069)	(0.208)	(0.069)
Immigration			-12.7***	0.681	-15.0***	0.428	-14.6***	0.510
			(3.75)	(1.18)	(3.79)	(1.13)	(3.77)	(1.13)
Migrant GP registrations			-1.71	1.54**	0.572	1.60**	0.178	1.46*
			(2.78)	(0.753)	(2.97)	(0.758)	(2.92)	(0.752)
White proportion					-3.11**	-0.584***	-3.22**	-0.642***
					(1.31)	(0.223)	(1.33)	(0.228)
Black proportion					-3.97*	-1.58***	-4.19**	-1.69***
					(2.04)	(0.361)	(2.05)	(0.367)
Asian proportion					-3.03**	-0.523**	-3.13**	-0.579**
					(1.41)	(0.239)	(1.43)	(0.244)
Domestic Migration					-2.77*	0.932***	-3.03**	0.822**
					(1.48)	(0.357)	(1.47)	(0.362)
Proportion with GCSE					-6.6×10^{-5}	-1.56×10^{-6}	-6.58×10^{-5}	-1.87×10^{-6}
					(0.0001)	(2.53×10^{-5})	(0.0001)	(2.52×10^{-5})
Proportion with A-Level					1.3×10^{-5}	-6.7×10^{-7}	1.07×10^{-5}	-1.4×10^{-6}
					(5.97×10^{-5})	(1.23×10^{-5})	(5.98×10^{-5})	(1.23×10^{-5})
No Education Qual.					-2.82***	-0.028	-2.81***	-0.040
					(0.634)	(0.167)	(0.635)	(0.168)
IMD score							-0.007	-0.003*
							(0.006)	(0.001)
Observations	12,712	12,712	10,217	10,217	10,217	10,217	10,217	10,217
R^2	0.98143	0.77419	0.98635	0.79666	0.98665	0.79851	0.98666	0.79909
Within R^2	0.07385	-0.00688	0.13218	0.00310	0.15083	0.01215	0.15141	0.01503
F-test (IV only)	1,012.4	40.039	631.38	15.548	565.23	11.591	535.99	8.6824
Wald (IV only), p-value	2.34×10^{-19}	1.35×10^{-5}	4.52×10^{-11}	0.00273	2.35×10^{-12}	0.00553	9.27×10^{-12}	0.01517
Electoral Ward fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

H Instrumental Variable Reduced Form Results

One way of assessing the extent to which our shift-share instrumental variable affects UKIP vote share through an unobserved variable (e.g. omitted variable bias) is by regressing UKIP vote share on the instrument, as well as the endogenous variable (inequality) and the control variables included in our specifications. The logic is that if the instrument affected UKIP vote share through a variable that was not included in our specifications, there would be an observable positive association between the instrument and UKIP vote share. We perform these regressions and present the results below in Table A4.

Table A4: Reduced Form Models of UKIP Vote Share in Local Elections

	UKIP vote share	UKIP vote share	UKIP vote share	UKIP vote share
RTB Shift-share IV	0.001	0.004	0.003	0.003
	(0.001)	(0.003)	(0.003)	(0.003)
GINI (standardized)	0.028***	0.026***	0.025***	0.025***
	(0.004)	(0.005)	(0.005)	(0.005)
Unemployment claims		0.017	0.020	0.020
		(0.013)	(0.013)	(0.013)
GDP per head		-0.045*	-0.047*	-0.047*
		(0.022)	(0.022)	(0.022)
Gross disposable income		-0.111*	-0.098+	-0.094+
		(0.051)	(0.051)	(0.054)
Immigration		0.395	0.161	0.163
		(1.122)	(1.090)	(1.099)
Migrant GP registrations		1.356+	1.435*	1.468*
		(0.734)	(0.728)	(0.738)
IMD score		-0.002	-0.003+	-0.003+
		(0.001)	(0.001)	(0.001)
White proportion			-0.710**	-0.700**
			(0.230)	(0.229)
Black proportion			-1.780***	-1.767***
			(0.364)	(0.362)
Asian proportion			-0.649**	-0.641**
			(0.246)	(0.245)
Domestic Migration			0.784*	0.772*
			(0.354)	(0.356)
Proportion with GCSE				0.000
				(0.000)
Proportion with A-Level				0.000
				(0.000)
No Education Qual.				-0.099
				(0.147)
Num.Obs.	12402	9908	9908	9908
R2	0.776	0.794	0.796	0.796
R2 Adj.	0.670	0.675	0.677	0.677
R2 Within	0.008	0.012	0.019	0.019
R2 Within Adj.	0.008	0.011	0.017	0.017
AIC	-33873.8	-26739.7	-26805.8	-26800.8
BIC	-4134.2	-542.1	-579.4	-552.8
RMSE	0.04	0.04	0.04	0.04
Std.Errors	by: Ward	by: Ward	by: Ward	by: Ward
FE: Ward	X	X	X	X
FE: Year	X	X	X	X

I Understanding Society Panel

We estimate two sets of models using the USOC panel data. Both sets use Equation 2. The first set of models presented in Table A5 use individual fixed effects, while the second set of models presented in Table A6 use LSOA fixed effects. LSOAs are census output areas that have about 1000-3000 residents. LSOAs constitute the lowest geographic identifier available in our dataset.

Table A5: Effects of Inequality on UKIP/Reform Party Vote (Individual FEs)

	UKIP/Reform Party Vote			
	(1)	(2)	(3)	(4)
Gini (standardised)	0.008***	0.009***	0.009***	0.010***
	(0.002)	(0.002)	(0.003)	(0.003)
IMD Score		0.0004*		0.0007**
		(0.0002)		(0.0003)
International Migration (per capita)			-0.311	-0.560
			(0.444)	(0.535)
Migrant GP Registrations (per capita)			0.175	0.404
			(0.401)	(0.424)
Employment Rate				0.0009
				(0.0009)
Unemployment Claimant Count				-0.003**
				(0.001)
Economic Inactivity Rate				0.0005
				(0.0010)
Gross Median Weekly Pay				9.49×10^{-5}*
				(4.9×10^{-5})
GDP per Person				-1.37×10^{-7}
				(1.26×10^{-7})
Observations	96,335	85,244	75,571	65,728
R^2	0.59244	0.60218	0.63455	0.64091
Within R^2	0.00020	0.00026	0.00020	0.00063
Individual fixed effects	✓	✓	✓	✓
Survey Wave fixed effects	✓	✓	✓	✓

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table A6: Effects of Inequality on UKIP/Reform Party Vote (LSOA FEs)

	UKIP/Reform Party Vote			
	(1)	(2)	(3)	(4)
Gini (standardised)	0.025***	0.025***	0.029***	0.022***
	(0.005)	(0.005)	(0.006)	(0.007)
IMD Score		0.002***		0.002***
		(0.0005)		(0.0007)
International Migration (per capita)			-2.31***	-2.81***
			(0.629)	(0.666)
Migrant GP Registrations (per capita)			1.01*	0.539
			(0.589)	(0.640)
Employment Rate				-3.49×10^{-5}
				(0.0010)
Unemployment Claimant Count				-0.006***
				(0.001)
Economic Inactivity Rate				-0.0004
				(0.001)
Gross Median Weekly Pay				0.0001
				(7.01×10^{-5})
GDP per Person				-6.71×10^{-7}**
				(3.07×10^{-7})
Observations	96,335	85,244	75,571	65,728
R^2	0.35620	0.37051	0.38496	0.39657
Within R^2	0.00044	0.00072	0.00064	0.00136
LSOA fixed effects	✓	✓	✓	✓
Survey Wave fixed effects	✓	✓	✓	✓

Significance levels: $*$ p < 0.05, $**$ p < 0.01, $***$ p < 0.001. Format of coefficient cell: Coefficient (Std. Error)

J USOC Event Study Results

Estimates for the dynamic effects of new, high-value properties are presented in Table A7. The estimates are derived from the Understanding Society Dataset and include the time five years before and after a new, high-value home is built.

Table A7: Effects of Inequality on UKIP/Reform Party Vote (Individual FEs)

	UKIP/Reform Party Vote			
	(1)	(2)	(3)	(4)
Year = -4	-0.010	-0.003	0.006	0.009
	(0.013)	(0.015)	(0.018)	(0.021)
Year = -3	-0.008	-0.0009	0.008	0.002
	(0.010)	(0.011)	(0.015)	(0.016)
Year = -2	-0.008	-0.004	0.005	0.007
	(0.008)	(0.010)	(0.013)	(0.014)
Year = 0	0.001	0.005	-0.004	-0.0008
	(0.008)	(0.009)	(0.012)	(0.012)
Year = 1	0.022**	0.024**	0.036**	0.034*
	(0.011)	(0.012)	(0.016)	(0.017)
Year = 2	0.039***	0.038**	0.051***	0.049**
	(0.014)	(0.015)	(0.019)	(0.021)
Year = 3	0.018	0.011	0.022	0.005
	(0.017)	(0.018)	(0.022)	(0.024)
Year = 4	0.016	0.013	0.023	0.007
	(0.020)	(0.021)	(0.026)	(0.030)
IMD Score		9.59×10^{-5}		0.0006
		(0.0008)		(0.001)
International Migration (per capita)			0.584	0.010
			(2.10)	(2.03)
Migrant GP Registrations (per capita)			-2.22	-1.20
			(1.65)	(1.66)
Employment Rate				0.003
				(0.002)
Unemployment Claimant Count				0.003
				(0.007)
Economic Inactivity Rate				0.003
				(0.003)
Gross Median Weekly Pay				-4.47×10^{-5}
				(0.0002)
GDP per Person				-8.24×10^{-7}
				(7.26×10^{-7})
Observations	20,464	18,094	15,705	13,719
R^2	0.71189	0.72256	0.74024	0.74290
Within R^2	0.01852	0.01910	0.01680	0.01894
Individual fixed effects	✓	✓	✓	✓
Survey wave fixed effects	✓	✓	✓	✓