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The Rise and Fall of the Price-to-Rent Ratio: Why Are Superstar Cities Different?*

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Abstract

In most countries, during the 2000s and 2010s, house prices rose substantially relative to rents. This trend, however, was not uniform across space or time. The price-to-rent ratio increased much more strongly in the countries' superstar cities, surged during economic expansion periods, but fell during times of economic crisis. These stylized facts are consistent with a model that features spatial variation in the supply price elasticity and autocorrelated local demand changes that trigger persistent changes in rent growth expectations. The model predicts that in supply-inelastic locations, positive (negative) demand shocks trigger increases (decreases) in the price-to-rent ratio that last several years. Stronger demand change persistence and lower discount rates amplify this effect. We test our model predictions employing panel data for England. Our instrumental variable first-difference estimates suggest that over half of the 153% increase in the price-to-rent ratio between 1997 and 2018 in Greater London can be explained by our mechanism.

JEL Classification: G12, R11, R21, R31, R52.

Keywords: House prices, housing rents, price-to-rent ratio, price and rent dynamics, housing supply, persistence in demand changes, expectations, discount rate, land use regulation.

1 Introduction

The new Millennium has brought with it a new crisis: the lack of affordable housing in many urban areas of the developed world, particularly in highly productive cities like London, New York, Paris, and Tokyo. The causes of this crisis, and especially of the strongly rising house prices in so-called 'superstar cities' – defined here as desirable, high-amenity cities with severely constrained housing supply – have been hotly debated amongst economists, with some pointing to laxer credit conditions and falling real interest rates and others to housing supply shortages. Whether price rises are primarily driven by cheaper mortgage financing, which might not affect the affordability of leveraged owner-occupied housing, or by tight land use restrictions and other supply constraints alongside demand growth, matters greatly from a policy point of view.

While rising house prices and rents both contribute to the growing affordability crisis, an intriguing fact is that in many – though not in all – countries, house prices have risen much more rapidly than rents during the 2000s and 2010s. This fact has been employed by some to suggest that there can be 'no supply shortage', as otherwise rents should have risen as much as prices.[1] A second stylized fact is that the increase in the price-to-rent ratio has been cyclical, rising during economic booms and falling during contraction phases. Both stylized facts are more pronounced in superstar cities.

Figure 1 illustrates this for England, France, the US, and corresponding superstar cities. Between 1997 and 2018, our sample period, the house price-to-rent ratio nearly doubled in England, increased by 84% in France, and rose by 21% in the US. In London and Paris, the price-to-rent ratio surged by a staggering 153% and 133%, respectively, while in New York City it more than doubled. In all these cases but more marked in the superstar cities, the price-to-rent ratio followed a cyclical pattern aligned with the business cycle. The dynamics differ notably in Japan (Panel D of Figure 1), a country experiencing a sustained population decline, resulting in decreased housing demand. There, the price-to-rent ratio has fallen over the same period, despite declining real interest rates. However, in Tokyo, where the population has been growing, the price-to-rent ratio increased by 60%, and it did so more cyclically.[2]

More broadly, price-to-rent ratio dynamics vary enormously across regions within countries. For England, Figure 2 shows that between 1997 and 2018, Greater London[3] experienced increases significantly above the national average, while the North East saw much smaller increases. The figure also reveals that the difference between the indices for London and the North East has followed a highly cyclical pattern.

In this paper, we propose a novel theoretical mechanism to explain why house prices can grow more strongly than rents over extended periods of time and why this increase can be expected

[1] The most prominent proponent in the UK is Mulheirn (2019). See also Been *et al.* (2019) who critically assess the 'supply skepticism' arguments in the US.

[2] According to the World Bank, Japan's real interest rate declined from 3.5% in 2000 to 1.1% in 2017. While Japan's lax planning system makes housing supply fairly price elastic, densely populated Tokyo faces stricter planning and limited developable land, significantly constraining housing supply.

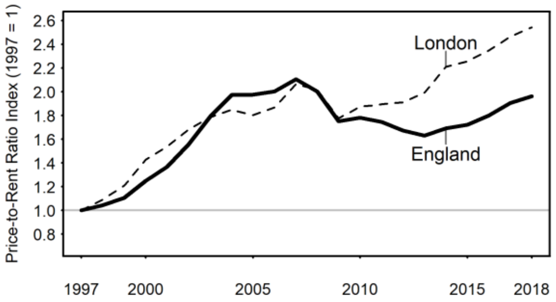
[3] By 'Greater London' or 'London' we mean the Greater London Authority, which consists of 32 local authorities.

to be cyclical and much more pronounced in economically thriving and tightly supply-constrained superstar cities, even when holding macroeconomic conditions constant.

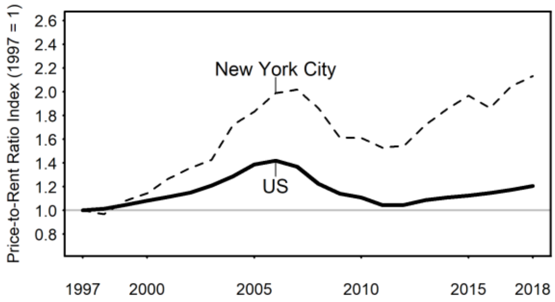
Figure 1

Price-to-Rent Ratio Indices for Selected Countries and Superstar Cities (1997-2018)

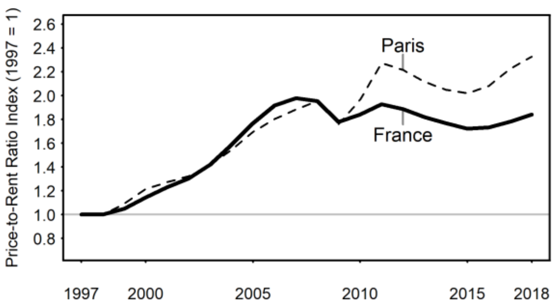
Panel A. England and London



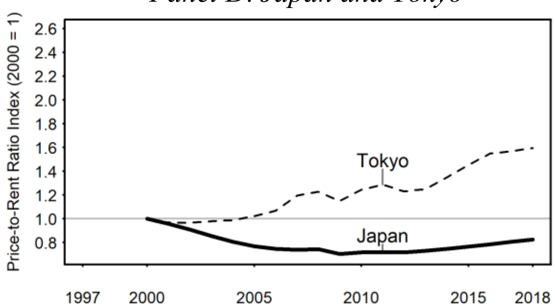
Panel B. United States and New York City



Panel C. France and Paris



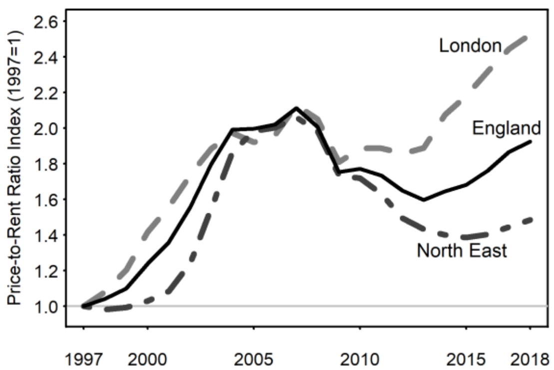
Panel D. Japan and Tokyo



Notes: The indices for England and London are based on transaction prices (Land Registry) and Private Registered Provider rents (Ministry of Housing, Communities & Local Government, Table 704). The indices for the US, France, and Japan are provided by the OECD (data series IDX2015 PRICERENT). The index for New York City is based on the NYU Furman Institute House Price Index for New York City and on a hedonic rent index compiled by the authors, based on mover households in the New York City House Condition and Vacancy Survey (rent controlled units excluded). For Paris, the rent index is provided by OLAP (free market rents) and the price index is provided by INSEE (transactions of second-hand housing units, ID 10567012). The city-level index for Tokyo is constructed from hedonic house price and rent indices for the 23 districts of Tokyo (based on Recruit Co. Ltd. listings data; indices provided to the authors by Chihiro Shimizu; see Diewert and Shimizu (2016) for details on the data).

Figure 2

Regional Price-to-Rent Ratio Indices in England



Notes: The figure displays the ratio of local house prices to rents, averaged over England, and over the Government Office Regions London and North East. House prices are based on transactions (Land Registry). Rents are Private Registered Provider rents (Ministry of Housing, Communities & Local Government, Table 704).

Under the standard assumption that the price of a house equals the sum of discounted expected future rental incomes, the price-to-rent ratio increases either when the discount rate falls *or when expected future rental incomes increase*.[4] Our theoretical framework focuses on the latter.

We develop a stylized dynamic model where locations are characterized by their housing supply constraints and changes in local housing demand exhibit serial correlation – a feature of our data. In this setting, a positive demand shock increases both contemporaneous and expected future rent growth. The impact on the latter depends crucially on the location's long-run housing supply constraints and demand change persistence: Tighter supply constraints and greater persistence push up expected future rents relative to contemporaneous rents, leading to a long-lasting but transitory rise in the price-to-rent ratio. This effect is amplified when the discount rate is low, as was the case after the Great Financial Crisis, because lower discount rates increase the present value of expected future rents. These propositions are consistent with the stylized facts illustrated in Figures 1 and 2.

In our empirical analysis, we examine the impact of the interaction between a local housing demand shifter – a Bartik (1991) shift-share measure of local labor demand – and the local long-run housing supply price elasticity on the dynamics of price and rent adjustments, as well as on the dynamics of the price-to-rent ratio during local economic booms and busts. We draw on rich panel data for England spanning over two decades, which enables us to study repeated housing cycles and yearly changes in the demand shifter. The focus on autocorrelated demand changes is critical, as they play a key role in the underlying theoretical mechanism. To deal with the potential endogeneity of the supply price elasticity, we employ an instrumental variables strategy, building on Hilber and Vermeulen (2016).

We focus on England for three main reasons. First, we have extremely detailed data – a unique panel dataset consisting of 353 Local Planning Authorities (LPAs) and annual data from 1997 to 2018.[5] Second, England provides a particularly relevant laboratory to study the determinants of real house price and rent growth. Since 1970, real house prices have grown more strongly in the UK, and particularly in England, than in any other OECD country and England does not control private rents.[6] Third, the severity of the affordability crisis in Greater London – the country's most productive and supply-constrained region – has fueled an exceptionally fierce political debate over the drivers of rising real house prices.

Our empirical analysis reveals five key insights, all consistent with our proposed theoretical mechanism. First, positive changes in labor demand increase both house prices and rents, with a stronger effect on prices. The latter is explained by the persistence of demand changes and

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[4] This holds true in the well-known Gordon Growth Model, where the price-to-rent ratio depends on the discount rate and expected long-run future rental growth. The Gordon Growth Model, however, makes important simplifying assumptions – e.g., constant expected rent growth in perpetuity – and does not explicitly take into account housing supply constraints. This limits the model's usefulness in explaining the dynamics of the price-to-rent ratio in local housing markets, where housing supply price elasticities differ and demand is cyclical.

[5] LPAs are the local authorities (also called 'councils') responsible for the execution of land use planning policy. Given that local regulatory restrictiveness varies across LPAs, they are the logical geographical unit for our analysis. LPAs contain on average 53,158 households, according to the 1991 Census. All data is matched to 2001 LPA boundaries.

[6] Own calculations based on data from the Bank for International Settlement, World Bank and Bank of England. Our analysis focuses on England rather than the entire UK because consistent planning data is only available for England. Within England, real price growth has been most staggering in London and the South East.

the resulting expected future rent increases. Second, the price-to-rent ratio may rise or fall in response to positive labor demand changes, depending on the long-run supply price elasticity and the persistence of demand changes. Third, the price-to-rent ratio responds more positively to demand changes in locations with inelastic long-run supply, reflecting the role of limited supply adjustments in shaping expectations of future rental incomes. Fourth, this interaction effect with the long-run supply price elasticity is stronger in areas with more persistent labor demand changes. Fifth, the interaction effect is more pronounced in the second half of our sample period, when long-term real interest and mortgage interest rates reached historical lows.

To explore the direct link between contemporaneous demand growth and rent growth expectations, we employ a novel dataset capturing shorter- and longer-term rent growth expectations of chartered surveyors advising potential house buyers and renters in England. We document that labor demand changes have a stronger impact on longer-run rent growth expectations in areas characterized by strong demand change persistence and inelastic long-run housing supply, consistent with our proposed theoretical mechanism.

The impact of supply constraints on the price-to-rent ratio is quantitatively important. In Greater London, where supply is seriously constrained, local demand changes combined with the local supply price elasticity explain 52.7% of the increase in the price-to-rent ratio between 1997 and 2018, while year fixed effects account for the remaining 47.3%. The relative contribution of local vis-à-vis macro factors varies over time. Between 1997 and 2007, when the average long-term real interest rate in England was 3.3%, local factors explain 32.3% of the increase in the price-to-rent ratio. However, local factors fully explain the increase from 2009 to 2018, when the average long-term real interest rate was 0.4%. Outside Greater London, where supply is more price elastic, the pattern is reversed. Here, the year fixed effects capture most of the, albeit much smaller, increase in the price-to-rent ratio between 1997 and 2018.

The year fixed effects are a 'black box'. They are likely to comprise the direct effect of changing real interest rates and other credit conditions. Because we standardize the supply price elasticity in our regressions, the year fixed effects also capture the impact of persistent aggregate changes in housing demand over the business cycle in conjunction with the average supply price elasticity in England. This is especially important in a country like England, where housing supply is relatively inelastic by international standards. Our empirical model suggests that by 2018 the price-to-rent ratio reverted to its 1997 level in English LPAs with relatively elastic housing supply, at the 95th percentile of our data.

We explore in detail several alternative mechanisms as potential explanations for our key findings: rising income inequality in segmented rental and owner-occupied markets, changing financing costs, varying land value shares and structure depreciation, changes in idiosyncratic investment risk, relaxation of financial constraints due to positive income shocks, shocks to local credit availability, deregulation of credit markets, sticky rents, and London-specific unobserved factors such as changing global demand for second homes. Our analysis reveals that these alternative mechanisms cannot account for our main findings.

We conduct several sensitivity checks to demonstrate the robustness of our results to the use of different instrumental variables, alternative rent measures, and to employing the change in the log price-to-rent ratio as an outcome. In addition, we perform a placebo exercise to address endogeneity concerns arising from potential correlations between changes in unobserved confounders and the initial industry composition used to construct our labor demand measure.

Our paper ties into – and helps reconcile disagreements between – two strands of a growing literature on the root causes of the housing affordability crisis that has emerged since the late 1990s, especially in superstar cities.

The first strand, mainly an urban economics literature, highlights the supply side and the micro-location; in particular, the role of binding local land use restrictions. It suggests that the rise in real house prices in desirable cities is largely the result of tighter local planning constraints in conjunction with strong demand growth. Most studies focus on the US and find a causal effect of land use regulation on house prices (e.g., Glaeser and Gyourko 2003, Glaeser *et al.* 2005a and 2005b, Quigley and Raphael 2005, Glaeser *et al.* 2008, Saks 2008, Saiz 2010, Baum-Snow and Han 2024), in particular, in superstar cities (Gyourko *et al.* 2013).[7,8] In the UK, various studies and reviews (e.g., Cheshire and Sheppard 2002, OECD 2004, Barker 2004 and 2006, Cheshire and Hilber 2008, Hilber and Vermeulen, 2016) suggest that the decades-long undersupply of housing and the extraordinary growth in real house prices are linked to a dysfunctional planning system and a lack of tax-induced incentives to permit development.

A few studies from this literature – Gyourko *et al.* (2013), Büchler *et al.* (2021), and Molloy *et al.* (2022) – focus on the determinants of local price-to-rent ratios. Gyourko *et al.* (2013) attribute spatial differences in the level of the price-to-rent ratio to differences in long-run expected demand growth in combination with relatively inelastic housing supply. Büchler *et al.* (2021) and Molloy *et al.* (2022) both explore the role of local supply price elasticities for long differences in prices and rents during a period of rising housing demand. Büchler *et al.* (2021) find that prices react more strongly to long-run demand changes than rents and argue that this is because investors update their perceptions of local risk premia and expected rent growth, with the degree of updating depending on the share of sophisticated investors in a location. Molloy *et al.* (2022) show that long-run changes in prices are more strongly correlated with supply constraints than long-run changes in rents. They rationalize this with future demand growth permanently exceeding supply growth in supply-constrained locations.

The second strand, situated within the macro-finance literature, emphasizes the demand side and the financing of housing, again with a focus on the US. Part of this strand argues that the unprecedented availability of credit and a reduction in the housing risk premium may jointly explain much, if not all, of the increase in real house prices (Favara and Imbs 2015, Favilukis *et al.* 2017, Justiniano *et al.* 2019, Greenwald and Guren 2025, Mian and Sufi 2022). Notably, Greenwald and Guren (2025) argue that an expansion of credit can account for a significant fraction of the increase in the price-to-rent ratio prior to the Great Financial Crisis. Similarly, Mian and Sufi (2022) suggest that the credit supply expansion triggered speculation and

[7] However, Nathanson and Zwick (2017), show that in a setting where agents disagree about the magnitude of a positive shock, speculation can cause house prices to increase strongly in areas with elastic supply.

[8] A closely related literature explores house price dispersion in the US. Van Nieuwerburgh and Weill (2010) develop a dynamic equilibrium model that features wage dispersion and housing supply constraints to explain house price dispersion across metropolitan areas. Ganong and Shoag (2017) rationalize house price divergence with increasing housing regulations and decreasing supply price elasticities. Howard and Liebersohn (2023) investigate the impact of persistent regional divergence in economic growth on aggregate house prices and rents.

thereby amplified the housing cycle. Another part of this strand emphasizes the role of demand expectations in explaining the boom-bust-rebound cycle of the 2000s and 2010s (Kaplan *et al.* 2020, Jacobson 2022, Chodorow-Reich *et al.* 2024) and similar patterns in earlier decades (Howard and Liebersohn 2023). The theoretical mechanisms explored in Kaplan *et al.* (2020) and Chodorow-Reich *et al.* (2024) are particularly closely related to ours. Kaplan *et al.* (2020) propose an exogenous shift in beliefs about fundamentals as a driver of price-to-rent ratios, while Chodorow-Reich *et al.* (2024) instead assume 'diagnostic expectations' about underlying fundamentals, i.e., agents forming expectations based only on the recent past and allowing for over-optimism during the boom. The four studies highlighting the role of demand expectations collectively attribute a much smaller fraction of the development of prices and price-to-rent ratios to credit conditions.[9] Taken together, this second strand of the literature provides persuasive evidence that changes in credit supply, house price risk, and beliefs about fundamentals fueled the US house price cycle during the 2000s and 2010s.

Our paper makes three core contributions to these strands of the literature. First, we propose and test a straightforward theoretical mechanism – deriving three testable propositions – to explain the rise and fall of the price-to-rent ratio during the 2000s and 2010s, a dynamic most pronounced in supply-constrained superstar cities like London. Our mechanism emphasizes the importance of local demand- and supply-side fundamentals for contemporaneous rents and rent growth expectations, thereby adding to both the urban economics and macro-finance strands of the literature. Despite its simplicity, our model is capable of replicating the boom-bust-rebound cycle. While our empirical analysis focuses on the period between 1997 and 2018, the mechanism can more generally explain rising and falling price-to-rent ratios over time and the greater amplitude in superstar cities, as observed, for example, in the US (Glaeser 2013).

Second, we use novel data on rent growth expectations along with local price and rent data covering over two decades that have not been used in previous research on the determinants of price-to-rent ratios. This allows us to add empirical evidence to the debate on the root causes of the housing cycles of the 2000s and 2010s, which has so far centered on the US. Our empirical analysis for England sheds light on the dynamic nature of the price-to-rent ratio during this period. Like Kaplan *et al.* (2020) and Chodorow-Reich *et al.* (2024), we emphasize demand and supply fundamentals as key determinants. Our empirical analysis focusing on local supply price elasticities and their role for the formation of rent growth expectations complements and extends the model-based evidence from that literature, not least by showing empirically that agents in the housing market form rent growth expectations based on these key factors. England represents a particularly interesting case, as the price-to-rent ratio rose significantly more during periods of economic expansion and fell more sharply during the downturn compared to the US. Moreover, using a rigorous empirical specification, we show that the largest swings occurred in locations where housing supply is least price elastic and demand change persistence is strongest, with low real interest rates amplifying these effects. More generally, our analysis reveals the importance of the supply price elasticity and of

[9] Consistent with this view, Glaeser *et al.* (2012) document that lower real interest rates can explain only one-fifth of the rise in US house prices between 1996 and 2006. Likewise, Himmelberg *et al.* (2006) and Glaeser (2013) suggest that the US housing boom of the 2000's can be well explained by demand and supply fundamentals.

demand change persistence for the formation of long-run rent growth expectations and thereby for the evolution of the price-to-rent ratio.

Third, we reject the 'no supply shortage' narrative. Our analysis shows that in supply-inelastic areas such as London, both prices and rents rose more strongly during economic boom periods. While price growth outpaced rent growth in these areas, this is well explained by our mechanism, which places supply constraints at its core. Indeed, we demonstrate that the long-run supply price elasticity is a crucial factor in explaining the rising price-to-rent ratio in England's superstar city, London, over our sample period.

Our paper is structured as follows. Section 2 presents our theoretical model and propositions. In Section 3, we introduce the data and empirical strategy, discuss the main empirical results, consider alternative explanations, and conduct robustness checks. We investigate the quantitative importance of the supply price elasticity in explaining differences in the dynamics of price-to-rent ratios across regions in Section 4. The final section concludes.

2 Theory

To explain why not only house prices and rents but also the price-to-rent ratio responds more strongly to demand shocks when housing supply is tightly constrained, we develop a stylized dynamic model of a local housing market with an infinite number of periods. It describes a representative location characterized by short- and long-run housing supply constraints that are constant over time.

Our theoretical mechanism builds on four crucial assumptions. First, changes in local housing demand exhibit persistence, which is a feature of our data. Second, because of binding short-run planning and construction lags, rents increase more strongly in response to unexpected than to expected demand changes. Third, locations differ in their long-run housing supply constraints and hence in their long-run supply price elasticity. Lastly, agents form rational expectations about future rent growth based on long-run supply constraints, observed demand changes, and demand change persistence.[10]

We assume that an exogenous shifter of local housing demand, D_t, evolves stochastically over time according to the law of motion

$$D_t = D_{t-1} + \rho \Delta D_{t-1} + e_t, \tag{1}$$

where $\rho > 0$ captures persistence in demand changes.[11] In our empirical setting, the equivalent of D_t is a shift-share measure capturing local labor demand, which plausibly affects local housing demand but is exogenous to local housing market conditions. e_t is a shock with expectation equal to zero. It permanently shifts the level of D_t.

[10] To keep the model simple, agents in our framework are assumed to be rational and fully aware of the state and history of demand, as well as the model parameters. In practice, agents' perceptions of the persistence of demand changes may differ from the actual degree of persistence – particularly if they are overly optimistic, as in Chodorow-Reich *et al.* (2024). To account for this in the empirical analysis, we use an estimate of the perceived degree of rent growth persistence based on survey data capturing rent growth expectations in English regions. Moreover, we abstract from extrapolation, search frictions, and credit mechanisms.

[11] The assumption of autocorrelated changes in local demand is motivated by the time series properties of (local) business cycles, where autocorrelation may result from labor adjustment costs (see e.g., Cogley and Nason 1995).

The rent level R_t of the location depends on long- and short-run housing supply constraints represented by parameters $\beta \geq 0$ and $\gamma > 0$, respectively, where $\gamma > 0$ implies supply is more inelastic in the short run than in the long run.[12] We define rents in period t as

$$R_t = 1 + \beta D_t + \gamma e_t. \tag{2}$$

Larger values of β and γ imply stronger contemporaneous and expected future rent increases in response to demand changes. The unexpected component of the demand shock pushes up rents by $(\beta + \gamma)e_t$. A larger β and a higher level of D_t imply higher rents.[13]

Expected future rents $j > 0$ periods ahead are $E_t[R_{t+j}] = 1 + \beta\left(D_t + \Delta D_t \sum_{k=1}^{j} \rho^k\right)$.

Here, the persistence in demand changes, ρ, is identical to the persistence in expected rent changes, provided $\beta > 0$. In real-world contexts, this transmission process is likely more complex, e.g., because rents may adjust slowly, i.e., they are 'sticky', or because agents in the housing market may become overly optimistic about the evolution of future demand. What is central to our mechanism is the fact that contemporaneous shocks to demand trigger persistent changes in rent growth expectations. In Section 3, we provide direct empirical evidence for this link, as well as for the degree of persistence in rent growth expectations.

We now consider the case where we are in an initial equilibrium with $\Delta D_{t-1} = 0$. Moreover, we assume that $D_{t-1} = 0$ to keep the derivations parsimonious. Using $\sum_{k=0}^{j} \rho^k = \frac{1-\rho^{j+1}}{1-\rho}$, the price of housing is given as the discounted stream of expected future rental income,

$$P_t = \frac{1+r}{r} + \frac{\beta e_t}{1-\rho} \sum_{j=0}^{\infty} \frac{1-\rho^{j+1}}{(1+r)^j} + \gamma e_t, \tag{3}$$

where r is the discount rate. Solving the sum term and simplifying, we get

$$\frac{P_t}{R_t} = \frac{\frac{1+r}{r} + \left(\beta \frac{(1+r)^2}{r(1+r-\rho)} + \gamma\right) e_t}{1 + (\beta + \gamma) e_t}. \tag{4}$$

The above expressions yield the following testable predictions:

PROPOSITION 1. *Consider a positive housing demand shock $e_t > 0$. House prices increase, and this rise is more pronounced if the long-run housing supply in the location is more constrained, i.e., less price-elastic.*

Proof: By inspection of equation (3).

[12] In the short run, supply is severely constrained as it takes time to plan and build new housing. These immediate constraints are no longer relevant in the long run. Still, supply can be constrained by physical, topographical, and long-run regulatory constraints (e.g., due to Not In My Backyard-behavior). While the parameter β pins down the long-run response of future rents to a demand shock, $\beta + \gamma$ determines the short-run response.

[13] Instead of defining the rent as a linear function of the demand shifter, we could also define the rent to be log-linear in the demand shifter, as we do in our simulations below. In that case, the price-to-rent ratio does not depend on the initial level of the demand shifter. However, such a formulation of the model does not lend itself to analytically deriving predictions about the price-to-rent ratio.

PROPOSITION 2. *Consider a positive housing demand shock* $e_t > 0$. *Rents increase, and this rise is more pronounced if long-run housing supply in the location is more constrained, i.e., less price-elastic.*

Proof: By inspection of equation (2).

PROPOSITION 3. *Consider a small positive housing demand shock* $e_t > 0$.

(i) *The price-to-rent ratio increases in response to a positive demand shock if long-run housing supply is sufficiently constrained. The increase is more pronounced if the long-run housing supply in the location is more constrained, i.e., less price-elastic.*

(ii) *Stronger autocorrelation of the demand changes amplifies the interaction effect of the demand shock with long-run housing supply constraints.*

(iii) *The interaction effect of the demand shock with housing supply constraints is more pronounced when the discount rate decreases.*

Proof: See Online Appendix A.

The intuition behind these results is as follows: Prices and rents are affected by a change in demand through long- and short-run supply constraints captured by β and $\beta + \gamma$, respectively. However, prices also depend on expectations about future rent growth, which are higher if long-run housing supply in the location is more tightly constrained (large β), or if future demand is expected to grow more strongly due to greater persistence in demand changes (large ρ). Therefore, long-run supply constraints and demand persistence push up expected future rental income and hence prices relative to current-period rents. Moreover, the expected future rental income has a higher present value if the discount rate is low (small r). This amplifies the interaction effect of the demand shock with β for prices but not for rents.

The price-to-rent ratio can decrease in response to a shock if $(\beta(1 + r) + \gamma)\rho < \gamma(1 + r)$, see Online Appendix A. Since short-run supply is relatively less elastic than long-run supply (i.e., $\gamma > 0$), this occurs if either persistence is low (i.e., ρ is sufficiently close to zero) or if long-run supply is relatively elastic (i.e., β is sufficiently close to zero). The underlying reason is that the increase in the contemporaneous rent triggered by the shock can exceed the change in the price if γ is large relative to β and ρ. As Sections 3 and 4 show, this case is empirically relevant, even in parts of England, which is generally characterized by comparably tight supply constraints.

In the model, the impact of an initial demand shock on the price-to-rent ratio is transitory, even though the shock causes a permanent shift in underlying demand. This is because expected future changes in demand that follow from the initial shock fade out over time as $\rho < 1$.[14]

Finally, our empirical analysis considers local business cycles and local supply constraints. However, the model mechanism, in principle, also applies at the macro level. That is, changes in the aggregate price-to-rent ratio could either be driven by discount rates, by some other macroeconomic factor, such as changing credit conditions, or by persistent changes to housing demand at the macro level, combined with aggregate housing supply constraints.

[14] This would be different in a version of the model where D_t exhibits trend growth and the innovations e_t affect trend growth rather than D_t itself. Kaplan *et al.* (2020) develop a similar idea where agents hold 'beliefs' about long-run housing demand growth, and these beliefs may shift between a high- and a low-demand regime.

3 Empirical Analysis

3.1 Data and Descriptive Statistics

We compile a panel data set at LPA level covering the years 1997 to 2018. We discuss the key variables below and provide more detailed information on the construction and sources of these variables in Online Appendix B. Table B1 reports summary statistics.

House Prices, Rents, and Price-to-Rent Ratio

The main outcome variable in our analysis is the price-to-rent ratio at LPA level. We construct this variable from housing transaction prices and rents, deflated by the national level retail price index net of mortgage payments (RPIX). For house prices, we build on Hilber and Vermeulen (2016) and use transaction data from the Land Registry to calculate a mix-adjusted real house price index at LPA level covering the period from 1997 to 2018.

We employ two measures for local rents. The first is the mean private market rent, provided by the Valuation Office Agency. Private market rents are available from 2010 to 2018. We construct a mix-adjusted real rent index that holds constant the average housing unit size (number of rooms). While private market rents are in principle our preferred measure of local rents, the fact that these data are only available for nine years is a significant limitation. We therefore employ a second measure – Private Registered Provider (PRP) rents – which yields a much longer time-series. PRP rents are provided by the Ministry of Housing, Communities & Local Government (MHCLG) and are available from 1997 to 2018. Some PRPs are for-profit organizations, others are not-for-profit. In all cases however, they have an incentive to maximize their rental income, subject to constraints; not-for-profit organizations to be able to reinvest surplus income to provide additional housing. All PRPs face a rent ceiling. This ceiling is typically defined as a fraction of the market rent that a particular unit would obtain on the free market. Because PRP rents allow us to cover a period of 22 years, with several (local) booms and busts, as opposed to only 9 years, we employ this measure in our baseline analysis.

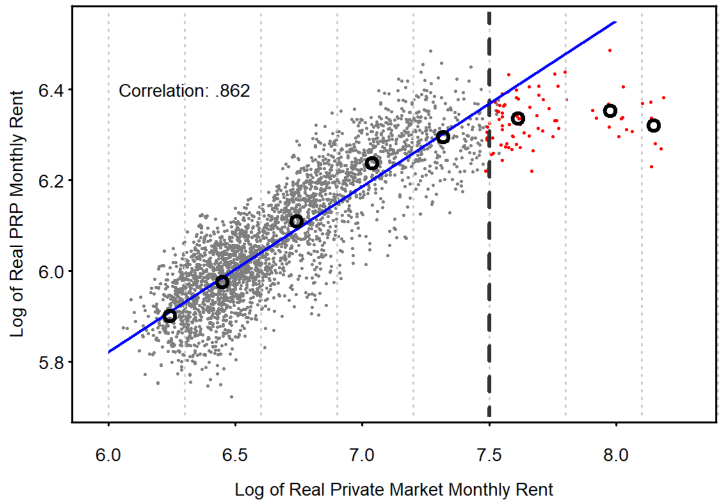
One may be concerned that PRP rents are not a good proxy for market rents. To assess this, Figure 3 depicts a scatterplot of the two measures by LPA and year, suggesting a strong positive relationship, except for LPAs with a very high private market rent (to the right of the dashed vertical line). The figure also displays averages for equally sized bins (bold black rings) that further support this conjecture. This suggests that PRP rents adequately capture the private market rent dynamics for the vast majority of LPAs in our sample.

To deal with the possibility that PRP rents may not adequately proxy for private market rents in LPAs with very high private market rents, we use a simple exclusion rule based on a visual inspection of Figure 3: We drop all LPAs with a mean log market rent exceeding 7.5. We use this smaller sample of LPAs for our baseline estimates.

In our baseline regression, we thus measure the local price-to-rent ratio as the ratio of average house prices to average PRP rents. As Table B1 shows, this measure of the price-to-rent ratio produces relatively large values, a direct consequence of the PRP rent ceiling. We run a series of robustness checks using alternative rent measures. These regressions – discussed in Section 3.6 – show that our baseline results are robust to the choice of the rent measure.

Figure 3

Private Registered Provider and Market Rents Scatterplot and Correlation



Notes: The graph plots the log of the real market monthly rent against the log of the real Private Rental Provider monthly rent, in each LPA and year. The bold black rings represent averages for the bins defined by the vertical light grey dashed bars. Each bin has a width of 0.3, starting at 6.0. The red dots indicate LPAs excluded from the regression sample because the relationship between the two types of rents differs from the relationship in other LPAs. Average log real market rents in these LPAs exceeded 7.5.

Long-Run Housing Supply Constraints

We use three measures to capture local long-run constraints to the supply of housing. Building on the literature (Burchfield *et al.* 2006, Saiz 2010, Hilber and Vermeulen 2016) we employ measures that capture regulatory, physical/geographical, and topographical long-run supply constraints, respectively. Our measure of regulatory restrictiveness is the average refusal rate of major residential planning applications from 1979 to 2018 derived from the MHCLG. Our two other supply constraint measures are taken from Hilber and Vermeulen (2016): the share of developable land already developed in 1990 and the range in elevation in the LPA, as a proxy for terrain ruggedness, which makes building costlier and thus represent a physical constraint to housing supply. The refusal rate and share developed measures are arguably endogenous. We therefore employ an instrumental variable strategy, discussed below.

Long-Run Supply Price Elasticities

We employ the three supply constraints measures and consider long-run changes in house prices and the housing stock, from 1981 to 2011, to estimate local supply price elasticities following Saiz (2010). Details are provided in Online Appendix B. The estimated elasticities for all LPAs are available for download here. The use of a single supply price elasticity measure allows us to more closely link the empirical analysis to our theoretical framework, where the relationship between the demand shifter and long-run expectations about rents critically depends on the parameter β, which is closely related to the inverse supply price elasticity.

Panel A of Figure 4 displays the distribution of the supply price elasticity across all LPAs in England, ranging from 0.15 for the City of London to 3.40 for St. Edmundsbury in the East of England. LPAs in the Greater London Authority, indicated by the red vertical bars, exhibit much lower elasticities compared to most other LPAs in England. The unweighted and household-weighted average supply price elasticities across all LPAs are 1.14 and 1.03, respectively, whereas both the unweighted and weighted average across London's LPAs is 0.28 Notably, London shares this feature with superstar cities in other countries, where supply price elasticities are typically much lower than the national average (e.g., Saiz 2010).

Measure of Local Housing Demand

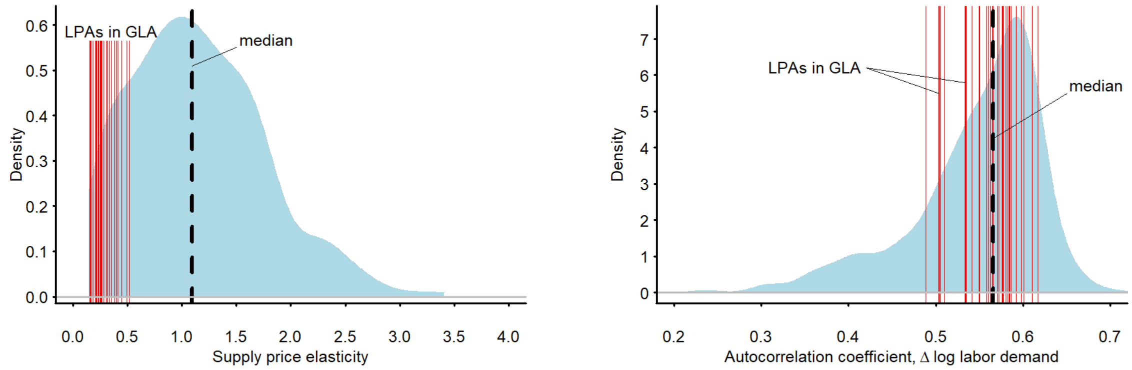
As a shifter of local housing demand, the D_t in our model, we use a Bartik (1991) shift-share measure of local labor demand, described in detail in Online Appendix B.

Our theoretical model assumes that changes in local housing demand are persistent. We test this assumption by regressing the change in log labor demand on its lag and a constant, separately for each LPA, using the full period for which the shift-share measure is available. Panel B of Figure 4 illustrates the spatial distribution of the estimated persistence parameters. Differences in persistence across LPAs arise from variations in the local industry composition and industry-specific degrees of persistence. LPAs in London, represented by the red vertical bars, exhibit a median persistence of 0.57, identical to the overall median, which is comparable to the degree of persistence found for similar demand measures in the US, e.g., Strobel *et al.* (2020). Overall, this suggests that the significantly stronger increase in the price-to-rent ratio in London compared to the rest of the country during our sample period is likely driven by a lower supply price elasticity rather than by differences in demand change persistence.

Figure 4

Spatial Distribution of Local Supply Price Elasticities and Persistence in Demand Changes

Panel A. Supply Price Elasticities *Panel B. Demand Shock Persistence*



Notes: The figure shows kernel density plots for the distribution of supply price elasticities in Panel A, and for the distribution of persistence of changes in local labor demand in Panel B. Demand change persistence is estimated using the entire labor demand series covering 1978-2018. Vertical red bars indicate LPAs in London.

3.2 *Endogeneity Concerns and Identification Strategy*

To capture the mechanism proposed by the theoretical model, we need to isolate exogenous variation in local supply price elasticities from local housing demand and other confounders. Our identification strategy is three-pronged.

First, we exploit the panel structure of our data: We control for time-invariant confounders by running regressions in first differences, and we capture the impact of common macroeconomic shocks through year fixed effects.

Second, our shift-share measure of local housing demand transforms time-series variation at the national level into local shocks that are arguably orthogonal to the state of the local housing market. One advantage of this demand shifter over local earnings is that it does not depend on house prices through income sorting, therefore only capturing housing demand and not housing supply. One concern is that the initial industry composition in a location may correlate with unobserved shocks to the relative attractiveness of renting versus owning. Another concern is that the financial and real estate services sector significantly drives local labor demand, meaning the shift-share measure could inadvertently reflect local credit availability. We address these threats to identification in the robustness check section. Moreover, our baseline period (1981) pre-dates the sample period by 16 years, making it highly unlikely that the local industry composition in the baseline year is correlated with potential confounders.

Third, we use an instrumental variable strategy to identify the causal effects of local housing supply constraints and hence the supply price elasticity. One general threat to the identification of supply constraints is that they tend to be correlated with housing demand conditions (Davidoff 2016). Other endogeneity concerns relate more specifically to our measures of regulatory restrictiveness and scarcity of developable land.

Identifying Long-Run Regulatory Supply Constraints

To identify regulatory restrictiveness, we use the *average* local refusal rate of major residential planning applications from 1979 to 2018. We thereby implicitly assume that LPAs refusing a higher share of applications over the long run are more restrictive in nature, rather than being faced with consistently poorer applications.[15]

Planning decisions are the outcome of a political economical process (Hilber and Robert-Nicoud 2013). Moreover, a developer wishing to build in a very restrictive LPA likely faces higher expected administrative costs of applying and a lower chance of approval. If developers believe that the chances of a rejection are high, they may spend more time preparing applications for projects with a reasonable chance of acceptance and submit a smaller total number of applications in the first place. In this case, the refusal rate underestimates the true regulatory restrictiveness. To address these potential sources of endogeneity, we employ three distinct instruments and demonstrate that our results are robust to varying the combination of instruments used.

Our first instrument is the LPA share of greenbelt land in 1973.[16] Greenbelt land is primarily used for agricultural purposes and should not be confused with public parks, the main recreational attractions in English cities. It is de facto protected from development, but constitutes a large share of the land surrounding many English cities. LPAs that were assigned a large share of greenbelt land back in 1973 arguably were also those with strong cohorts of Not In My Backyard (NIMBY) residents who would subsequently fight hard to maintain the status quo. Thus, we expect the historic share of greenbelt land and local planning restrictiveness to be strongly positively correlated. However, the historic share of greenbelt

[15] Using the long-run average rather than annual data is important, as the number of planning applications varies with housing demand. When demand is high and the capacity of LPAs to process applications is limited, one strategy for managing excess workload may be to reject some applications quickly. As a result, the annual refusal rate tends to be pro-cyclical – rising during booms – and this pattern is clearly borne out in the data. To mitigate this bias, we rely on the long-run average refusal rate in our analysis.

[16] We calculate the share of (protected) greenbelt land in 1973 from a digitized historic map of Great Britain and a shapefile of the 2001 LPA boundaries. See Online Appendix B for more information.

land should not directly affect contemporaneous changes in the price-to-rent ratio, except through its impact on regulatory restrictiveness. The facts that it (i) substantially predates the sample period and (ii) is used for agricultural rather than recreational purposes make it unlikely to be correlated with contemporaneous demand conditions or other potential confounders.

Instruments two and three were originally proposed by Hilber and Vermeulen (2016) – for details see their paper. The second instrument exploits a 2002 reform of the English planning system. The reform imposed a speed-of-decision target for major developments on LPAs. Our identifying assumption is that the reform had a differential impact on more and less restrictive LPAs: More restrictive LPAs should have had a stronger incentive pre-reform to delay residential applications and a stronger incentive post-reform to reduce their delay rate. The change in the delay rate (post- vs. pre-reform) thus provides a policy-induced exogenous source of variation in regulatory restrictiveness.

Our third instrument is the Labour party vote share in the 1983 General Election, derived from the British Election Studies Information System. This and similar instruments have been used previously to identify planning restrictiveness (Bertrand and Kramarz 2002, Sadun 2015, Hilber and Vermeulen 2016). The average Labour voter is a renter and has below-average income and housing wealth. Consequently, this group likely prioritizes housing affordability and hence housing supply. Thus, we expect a negative correlation between the Labour vote share and local planning restrictiveness, all else equal.

In our baseline regression, we jointly include the three instruments. In robustness checks, we explore the sensitivity of the results to using only two or one of the three instruments.

Identifying the Share of Developed Land

The share of developable land that was developed in 1990 reflects the extent to which new development is likely to involve costly redevelopment rather than straightforward development on greenfield land. However, it may be endogenous to local demand conditions. Some places may have become more attractive over time due to better amenities or economic opportunities, leading to immigration from less desirable locations and a higher share of developed land in 1990. Similarly, the planning decisions of an LPA prior to 1990 could influence the amount of undeveloped land remaining in 1990. To address these potential sources of endogeneity, we adopt the strategy proposed by Hilber and Vermeulen (2016) and instrument the share of developed land in 1990 using population density in 1911. The rationale is that population density in 1911 is indicative of (time-constant) local amenities and the productivity of a place, which predicts the share of developed land almost 80 years later. However, its effect on average house prices and rents in an LPA will be netted out by first-differencing. Furthermore, historic population density is unlikely to correlate with changes in contemporaneous demand conditions. Thus, it is improbable that historic density influences changes in house prices and rents during the sample period through channels other than land scarcity.

3.3 Empirical Baseline IV-Specification

The theoretical propositions derived in Section 2 indicate that the impact of changes in local housing demand on local house prices, rents, and the price-to-rent ratio depends on the local long-run supply price elasticity. To empirically test this relationship, we estimate the following specification in first differences:

$$\Delta y_{it} = \sum_{k=0}^{3} \left(\theta_{0,k} \Delta LLD_{i,t-k} + \theta_{1,k} \Delta LLD_{i,t-k} \times elasticity_i \right) + \Delta HTB_{it} + \phi_t + v_{it}. \tag{5}$$

As outcomes y_{it}, we consider a log mix-adjusted real house price index, log real rents, and the price-to-rent ratio for LPA i and year t. The first-difference specification nets out time-constant local differences in housing market conditions. We include year fixed effects ϕ_t in all regressions to control for macroeconomic factors that vary over time, but not locally.

The main source of variation comes from changes in our shift-share measure of log local labor demand, ΔLLD. The contemporaneous change, ΔLLD_t, may comprise both a predictable and an unpredictable component that affect rents and prices. To separate the unpredictable component from the predictable one, our price-to-rent ratio baseline specification controls for three lags of ΔLLD_t (ΔLLD_{t-k}, $k = 1,2,3$), such that we can interpret the contemporaneous change as the unexpected component (i.e., as a 'shock'). When adding further lags, these cease to be statistically significant.

To account for a differential impact of local demand changes on the outcomes, we interact the ΔLLD_{t-k}'s with the supply price elasticity of LPA i, $elasticity_i$, which is standardized to have a mean of zero and a standard deviation of one. This allows for straightforward interpretation of the coefficients: $\theta_{0,0}$ captures the impact of ΔLLD_t on the outcome in an LPA with average supply price elasticity, while $\theta_{1,0}$ reflects the additional impact when the supply price elasticity is one standard deviation above the national average.

The supply price elasticity is estimated from three measures of supply constraints: the average refusal rate, the share of developed land, and the altitude range. To address potential endogeneity concerns related to the refusal rate and the share of developed land, we instrument the interaction of (lags of) ΔLLD_t with the supply price elasticity. The excluded instruments are interactions of (lags of) ΔLLD_t with the share of historic greenbelt land, the reform-induced change in the delay rate, the share of Labour votes in the 1983 General Election, historic population density in 1911, and the altitude range.

The regressions also control for a dummy variable ΔHTB_{it}, which equals one for LPAs in London in 2016 and zero otherwise. The dummy captures the spatially varied impact of the Help to Buy policy, which assists households purchasing homes through an equity loan scheme. In 2016, the policy became more generous in London compared to the rest of the country (Carozzi *et al.* 2024).[17] Since we estimate a first-difference equation, the dummy variable captures the differential effect of the policy for London LPAs upon its introduction in 2016, relative to the year before.

We cluster standard errors at the Travel to Work Area (TTWA) level to account for potential correlation of regression errors across LPAs within the same local labor market.

[17] The variable may also capture the impact of the Brexit referendum in 2016 to the extent that it affected London differentially.

3.4 Main Results

Prices and Rents

We first consider the impact of ΔLLD_t in conjunction with local supply constraints on real house prices and rents separately. Table 1 presents the baseline results, testing PROPOSITIONS 1 and 2. Before estimating the baseline specification defined in equation (5), we analyze the role of each supply constraint measure individually. The dependent variable in Columns (1) to (3) is the log change in the real house price index. In Column (1), estimation is by OLS. ΔLLD_t and its interaction terms with the refusal rate and the share of developed land are highly significant and positive, consistent with PROPOSITION 1. The interaction with the altitude range is negative, while the Help to Buy dummy is positive and significant.

Table 1

Impact of Changes in Labor Demand on Changes in House Prices and Rents

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	ΔLog price			ΔLog rent		
	OLS a), b)	IV a), b), c)	IV a), b), c)	OLS b)	IV b), c)	IV b), c)
ΔLog local labor demand	0.232***	0.163	0.284***	0.098	0.105*	0.101
(ΔLLD_t)	(0.082)	(0.102)	(0.095)	(0.063)	(0.062)	(0.066)
ΔLLD_t × refusal rate of major	0.362***	0.743***		0.050***	0.032	
residential projects	(0.051)	(0.072)		(0.018)	(0.033)	
ΔLLD_t × share developable	0.340***	0.706***		0.093***	0.124***	
land developed in 1990	(0.127)	(0.112)		(0.025)	(0.024)	
ΔLLD_t × range between	-0.196***	-0.020		0.004	0.017	
highest and lowest altitude	(0.046)	(0.082)		(0.028)	(0.028)	
ΔLLD_t × supply price elasticity			-0.757***			-0.095**
			(0.209)			(0.047)
ΔHelp to Buy dummy	0.021***	0.008*	0.017**	0.006***	0.005***	0.007***
	(0.006)	(0.005)	(0.007)	(0.001)	(0.001)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,211	7,211	7,211	7,211	7,211	7,211
Number of LPAs	344	344	344	344	344	344
Adjusted R-squared	0.768			0.442		
SW-F, ΔLLD_t × refusal rate		122.1			122.1	
SW-F, ΔLLD_t × share dev.		62.4			62.4	
SW-F, ΔLLD_t × elasticity			32.8			32.8

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. [a] Observations with missing rent data removed to make price and rent specifications comparable. [b] PRP vs. market rent outliers (mean log market rent > 7.5, based on Figure 3) removed. [c] First-stage results reported in Table C1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–2006, share of votes for Labour in 1983 General Election, and population density in 1911, all interacted with ΔLLD_t. Regressions in columns (3) and (6) employ the altitude range interacted with ΔLLD_t as additional excluded instrument. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016).

In column (2), we address the endogeneity concerns discussed above by estimating the same regression by Two-Stage Least Squares (2SLS), instrumenting the interactions of the refusal rate and the share developed measures with ΔLLD_t. The independent effect of ΔLLD_t and its interaction with the refusal rate and share of developed remain positive and highly significant, with coefficients that are quantitatively larger than the corresponding OLS estimates. The implied bias in the OLS estimates is consistent with developers not applying for planning approval in restrictive LPAs with high rejection rates. Sanderson and Windmeijer (2016) F-statistics do not indicate weak instruments.

Overall, the results are very similar to those obtained by Hilber & Vermeulen (2016), despite differences in the study period, the inclusion of the share of greenbelt land as an additional instrument to enhance identification of regulatory restrictiveness, and the use of a first-difference specification alongside a more refined measure of local labor demand.

We report the corresponding first-stage results in columns (1) and (2) of Table C1 in Online Appendix C. The instruments show strong and expected correlations with the refusal rate and the share developed interactions.

In column (3), we replace the three separate supply constraints measures with the supply price elasticity. The elasticity is included in standardized form and instrumented using the same set of instrumental variables as in column (2), plus the altitude range. The independent effect of ΔLLD_t is significantly positive, while its interaction with the supply price elasticity is significantly negative, as expected. According to this regression, an increase of log labor demand by one log point causes prices to increase by 0.284 log points in an average LPA and by 0.284 + 0.757 = 1.041 log points in an LPA with an elasticity one standard deviation (0.61) below the national average of 1.14. The corresponding first-stage results, which show that the instruments correlate strongly and in expected ways with the supply price elasticity interaction, are reported in column (3) of Table C1.

In columns (4) to (6), the dependent variable is the change in log real PRP rents. Qualitatively, the results are very similar to the price regression results, consistent with PROPOSITION 2, though the coefficients are smaller in magnitude. This suggests that local supply price elasticities play a relatively larger role in shaping the impact of ΔLLD_t on house prices than on rents, consistent with our theoretical framework.[18]

Price-to-Rent Ratios (Baseline Estimates)

In Table 2, we consider the change in the price-to-rent ratio as the dependent variable to test PROPOSITION 3(i). We begin by regressing the change in the price-to-rent ratio on the same set of explanatory variables used in Table 1. Column (1) reveals that the price-to-rent ratio rises in an average LPA in response to an increase in ΔLLD_t, with a stronger effect observed when regulatory (refusal rate) and physical (share of developed land, altitude range) supply constraints are tight. In column (2), ΔLLD_t is instead interacted with the supply price elasticity. This regression indicates a significantly positive independent effect of ΔLLD_t, while its interaction with the supply price elasticity is significantly negative, consistent with PROPOSITION 3(i).

[18] In locations with high supply price elasticities, the models in columns (3) and (6) predict negative impacts of demand shocks on prices and rents but they are never statistically significantly different from zero in the rent regression and only in relatively few cases in the price regression. We attribute this partly to statistical uncertainty, and partly to a potentially non-linear relationship between the estimated and the true underlying supply schedule.

Table 2

Determinants of the Change in the Price-to-Rent Ratio (Baseline Specification, 1997-2018)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ΔPrice-to-rent ratio				
	IV [a), b), c)]	IV [a), b), c)]	IV [b)]	IV [b)]	IV [b)] Baseline
ΔLog local labor demand (ΔLLD_t)	18.060*	27.556***	23.375**	24.743**	22.811**
	(10.945)	(10.404)	(10.984)	(10.317)	(10.790)
ΔLLD_{t-1}			-3.157	6.045	10.389
			(6.378)	(7.158)	(7.885)
ΔLLD_{t-2}				-25.315***	-21.164***
				(9.506)	(7.318)
ΔLLD_{t-3}					-6.017
					(8.403)
ΔLLD_t × refusal rate	66.707***				
	(5.243)				
ΔLLD_t × share developed	59.997***				
	(7.445)				
ΔLLD_t × altitude range	14.144**				
	(6.919)				
ΔLLD_t × supply price elasticity		-71.096***	-61.011***	-60.481***	-60.195***
		(10.439)	(8.771)	(8.726)	(9.030)
ΔLLD_{t-1} × supply price elasticity			-20.610***	-16.965***	-19.795***
			(3.897)	(4.772)	(4.980)
ΔLLD_{t-2} × supply price elasticity				-11.893***	-16.980***
				(4.337)	(5.964)
ΔLLD_{t-3} × supply price elasticity					11.730
					(8.242)
ΔHelp to Buy dummy	0.039	0.423	0.225	-0.383	-0.448
	(0.266)	(0.340)	(0.301)	(0.337)	(0.389)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,211	7,211	7,211	7,211	7,211
Number of LPAs	344	344	344	344	344
SW F, ΔLLD_t × refusal rate	122.1				
SW F, ΔLLD_t × share developed	62.4				
SW F, ΔLLD_t × elasticity		32.8	53.9	47.7	42.2
SW F, ΔLLD_{t-1} × elasticity			52.9	61.4	46.3
SW F, ΔLLD_{t-2} × elasticity				30.8	40.1
SW F, ΔLLD_{t-3} × elasticity					46.2

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. [a)] First-stage results reported in Table C1. [b)] Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and the altitude range (columns (2) to (5) only), all interacted with ΔLLD. [c)] PRP vs. market rent outliers (mean log market rent > 7.5, based on Figure 3) removed.

The first-stage results corresponding to columns (1) and (2) are reported in Table C1. They are identical to those reported for Table 1. Sanderson and Windmeijer (2016) F-statistics confirm that weak instruments are not an issue.

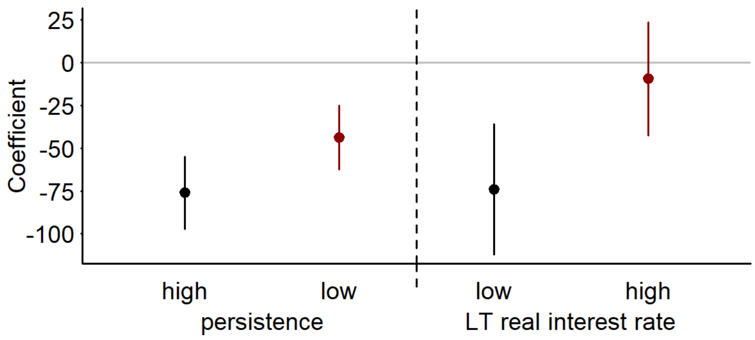
Columns (3) to (5) successively add controls for lags of ΔLLD_t and their interactions with the supply price elasticity, using as instruments the interactions of these lags with the instruments for the supply price elasticity. This way, we control for confounding effects of past changes of labor demand changes on the housing market and isolate the unexpected component of ΔLLD_t. These regressions reveal that most of the impact of ΔLLD_t on the price-to-rent ratio can be attributed to the unexpected component, again consistent with PROPOSITION 3(i). Sanderson and Windmeijer (2016) F-statistics again indicate that weak instruments are not a concern.

Heterogeneity in Persistence Across LPAs

PROPOSITION 3(ii) suggests that a higher persistence of ΔLLD_t amplifies the interaction effect of ΔLLD_t with the supply price elasticity. To test this proposition, we exploit the fact that certain industries are subject to shocks exhibiting greater persistence than others, resulting in differences in persistence across LPAs. We split our sample of LPAs at the median level of persistence (see Panel B of Figure 4) and estimate the baseline regression (column (5) of Table 2) separately for each half of the sample. The estimated interaction effects are presented in Figure 5, to the left of the vertical dashed line. Black and red dots indicate the point estimates of the interaction effects for LPAs with above- and below-median demand change persistence, respectively. The results lend support to PROPOSITION 3(ii), showing a significantly stronger negative interaction effect in high-persistence LPAs.

Figure 5

Interaction Effect of the Change in Log Local Labor Demand and the Supply Price Elasticity Depending on Persistence and Long-Term Real Interest Rates



Notes: The figure displays regression coefficients from estimating equation (5) for split samples. The dots to the left of the dashed vertical line represent estimates for LPAs with above- and below-median persistence (0.57) in ΔLLD. The estimates right of the dashed vertical line are based on a split of the sample into two 11-year periods: 1997-2007 (average long-term real interest rate of 3.3%) and 2008-2018 (average long-term real interest rate of 0.6%). The vertical bars indicate 95% confidence intervals, with clustering at the TTWA level.

Heterogeneity in Long-Term Real Interest Rates

PROPOSITION 3(iii) indicates that the interaction effect of the supply price elasticity with ΔLLD_t is larger during periods of low real interest rates. The intuition is that the elasticity influences the extent of the long-run supply response to ΔLLD_t, which in turn affects expected future rents. When future rental incomes are discounted less strongly (i.e., in a low-interest rate environment), spatial differences in elasticities become more important. To test this proposition, we split our sample period into two halves: 1997 to 2007 and 2008 to 2018. During 1997 to 2007, the average long-term real interest rate was 3.3%, but it dropped sharply to 0.6% on average between 2008 and 2018. To the right of the dashed line in Figure 5, the interaction effect is displayed for the low-interest rate environment in black and the higher-interest rate environment in red. The results support PROPOSITION 3(iii), showing a stronger negative interaction effect in the low-interest rate environment.

Rent Growth Expectations

In our theoretical framework, changes in demand influence future rent growth expectations because demand changes exhibit persistence. In this context, the supply price elasticity plays a key role by amplifying the impact of an initial shock on rent growth expectations. Given a fixed discount rate, the more inelastic the long-run supply, the more strongly house prices will respond to the initial shock relative to rents.

The results presented so far align with this argument. However, in our empirical analysis, we observe only ΔLLD_t, the varying persistence of these demand shifts, and supply price elasticities. We do not directly observe rent growth expectations at the LPA level. To test our proposed mechanism more directly, we leverage a unique data set provided by the Royal Institute of Chartered Surveyors (RICS), which asks surveyors about their shorter-run (12 months) and longer-run (5 years) rent growth expectations across the nine Government Office Regions (GORs) of England. While house purchase and rent decisions are ultimately made by households, households in England rely heavily on surveyors' assessments. The dataset spans the years 2013 to 2018. We deflate the rent growth expectations using the RPIX and geographically match these data at the regional level with our main panel. Panel E of Table B1 presents summary statistics for expected real rent growth one year ahead and for expected annual real rent growth over the next five years.

We regress the two rent growth expectations variables on ΔLLD_t, as well as interactions of ΔLLD_t with the (standardized) supply price elasticity and a dummy variable indicating above-median demand change persistence. We use OLS as IV estimates are underpowered due to the small sample size. The results, reported in Table 3, show that changes in regional labor demand induce agents in the market to update both their shorter- and longer-run rent growth expectations. Short-run rent growth expectations adjust more strongly in regions characterized by relatively inelastic supply. Additionally, while persistence does not have a statistically significant impact on one-year-ahead expectations, it is positive and statistically significant for five-year ahead expectations. These findings are robust to adding region and year fixed effects. Overall, these patterns are in line with our proposed theoretical mechanism.

In Table 4, we analyze the relationship between one-year-ahead and five-year-ahead annual rent growth expectations. We do so by regressing the expected annual rent growth rate over the next five years on the expected rent growth rate over the next 12 months. The table shows that a 1% higher expected rent growth over the next 12 months is associated with a roughly 0.9% higher expected average annual growth rate over the next five years. This finding is robust to the inclusion of fixed effects controlling for average changes by GOR and year.

The estimated coefficient provides insight into the degree of demand change persistence perceived by agents in the housing market. Letting ρ represent the degree of persistence in log demand changes and g denote contemporaneous expected rent growth over 12 months, the average expected rent growth over the next five years can be approximated[19] as $g \times (1 + \rho + \rho^2 + \rho^3 + \rho^4)/5$. Thus, the regression coefficients from Table 4 recover $(1 + \rho + \rho^2 + \rho^3 + \rho^4)/5$ and therefore pin down a value of ρ. Our preferred estimate of 0.909 in column (3), which includes both year and GOR fixed effects, implies $\rho \approx 0.95$. Importantly, in this context, g reflects deviations from expected rent growth by GOR and year, effectively netting out regional and aggregate trends.

Table 3
Changes in Labor Demand and Rent Growth Expectations at Regional Level

	(1)	(2)	(3)	(4)	(5)	(6)
	One-year-ahead rent growth expectation			Five-year-ahead annual rent growth expectation		
	OLS	OLS	OLS	OLS	OLS	OLS
Change in log regional labor demand (ΔLLD_t)	0.404***	0.405***	0.701	0.538***	0.538***	0.918
	(0.047)	(0.047)	(0.494)	(0.035)	(0.032)	(0.596)
ΔLLD_t × supply price elasticity	-0.283***	-0.308***	-0.236***	-0.228***	-0.260***	-0.158**
	(0.045)	(0.036)	(0.044)	(0.034)	(0.033)	(0.055)
ΔLLD_t × persistence	0.054	0.054	0.061	0.095***	0.095***	0.108**
	(0.051)	(0.048)	(0.046)	(0.033)	(0.028)	(0.035)
Region FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes
Observations	54	54	54	54	54	54
Number of GORs	9	9	9	9	9	9
Adj. R-squared	0.060	0.027	0.893	0.029	0.032	0.875

*Notes: S*tandard errors in parentheses clustered by GOR. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the regional rent growth expectation, measured one and five years ahead. Expectations are based on RICS survey data aggregated to GORs in England. All remaining variables are also aggregated to the regional level. The supply price elasticity and persistence are standardized to have a mean of zero and a standard deviation of one.

Table 4
Persistence of Regional Rent Growth Expectations

	(1)	(2)	(3)
	Annual rent growth expectation over the next five years		
	OLS	OLS	OLS
Rent growth expectation over next 12 months	0.897***	0.981***	0.909***
	(0.130)	(0.135)	(0.085)
Region FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	54	54	54
Number of GORs	9	9	9
Adj. R-squared	0.608	0.747	0.864

*Notes: S*tandard errors in parentheses clustered by GOR. *** p<0.01, ** p<0.05, * p<0.1.

The persistence of $\rho \approx 0.95$ backed out from these results is notably higher than the median degree of persistence we report in Figure 4 for changes in the shift-share labor demand measure. Several factors may explain this discrepancy. First, the degree of persistence we report in

[19] More precisely, one could construct an index with values $1 + g, 1 + g + \rho g, 1 + g + \rho g + \rho^2 g, \ldots$ and compute expected growth rates from this index. The differences to the simple average discussed in the text are negligible for quantitatively small values of g. We therefore use the simpler average as described in the text.

Figure 4 may be downward biased due to noise or measurement error in the shift-share measure. Second, the rent growth expectations of the RICS survey respondents may have been highly or even overly optimistic. Third, while the shift-share labor demand measure is arguable exogenous to local demand conditions, it only partially captures changes in overall local housing demand, which may exhibit a higher degree of persistence. Fourth, our persistence estimate assumes a simple autoregressive process for ΔLLD_t, a mathematically convenient approach that may not fully characterize the local housing demand cycle. Fifth, rents may adjust slowly in the short run, limiting the immediate impact of demand changes but contributing to stronger persistence in rent growth over time. Finally, in contrast to the comparably short RICS time-series, the shift-share labor demand measure contains turning points implying a lower degree of autocorrelation.

Can the Proposed Mechanism Quantitatively Account for the Observed Patterns?

The analyses presented so far confirm the proposed mechanism in a qualitative sense. We now examine whether it can also account for the observed magnitudes. Notably, Table 1 suggests that demand changes have a considerably smaller impact on rents than on prices. However, due to demand persistence, the initial impact on rents triggers higher rent growth expectations, which may cumulatively account for the relatively larger impact on prices. Tables 3 and 4 support this interpretation. Table 3 shows that persistent labor demand changes induce adjustments in long-run rent growth expectations, particularly in areas with inelastic supply and high persistence in labor demand changes. Table 4 demonstrates that rent growth expectations themselves exhibit a high degree of persistence.

In Table 5, we compare the differential impact of an initial demand shock on prices across LPAs with supply price elasticities one standard deviation below and above average, respectively (using column (3) of Table 1) to the implied price changes derived from the contemporaneous impact on rents (using column (6) of Table 1). This comparison incorporates the persistence of rent growth expectations from Table 4 and considers two discount rate scenarios. Details are given in Online Appendix A.

Table 5

Differential Impact of a Change in Log Labor Demand by One Log Point on Rents and Prices (Table 1) in Locations with Above- and Below-Average Supply Price Elasticity

Discount rate	Scenario 1 7.9%	Scenario 2 4.8%
Differential impact on prices implied by rent regression (column (6) of Table 1)	0.0159	0.0203
Differential impact on prices as estimated from the price regression (column (3) of Table 1)	0.0151	

Notes: The table compares a location where the supply price elasticity is one standard deviation below average to a location where it is one standard deviation above average. The impact on the price implied by the rent regression is computed as the discounted sum of the change in expected future rental income, assuming a persistence of expected rent growth of 0.95 derived from Table 4 and a ΔLLD_t of 0.01. The assumption about the discount rate is stated in each column. Details are given in Online Appendix A.

In Scenario 1, we set the discount rate to 7.9%, reflecting the average real mortgage interest rate of 4.4% between 1997 and 2007, a depreciation rate of 2%, and a risk adjustment of 1.5%.

Under this scenario, the differential impact of a demand change of one log point implied by the rent regression is 0.0159, which is close to the differential impact implied by the price regression (0.0151). In Scenario 2, we consider the period between 2008 and 2018, when the average real mortgage interest rate was 1.3%. Including depreciation and risk adjustments, this yields a discount rate of 4.8%. Here, the implied interaction term is somewhat larger, at 0.0203. Overall, under these realistic assumptions about the discount rate, informed by observed interest rates and insights from real estate finance, the implied and estimated impacts on prices are of similar magnitudes.

As an alternative approach, we use our theoretical framework to reassess whether the proposed mechanism can quantitatively explain the large swings in price-to-rent ratios across locations, as documented in Figure 2. Using the data to inform key parameter choices, we reverse-engineer the demand shocks required for the model to replicate the observed evolution of regional price-to-rent ratios between 1997 and 2018. Detailed simulations and results are provided in Online Appendix D.

The simulations indicate that the required shocks are small in magnitude, mostly ranging between -0.01 and 0.01, and align closely with the boom-bust cycles in the regional economies, as captured by the evolution of regional unemployment rates (see Online Appendix D and, in particular, Panel B of Figure D6). Moreover, the simulated differences in prices and rents across regions closely match the observed differences. Notably, the model is capable of replicating the stylized fact that prices rose and fell substantially more strongly in London than in the North East during the 2000s.[20]

The model generates rent expectations that can be compared to the survey evidence. From 2013 to 2015, survey respondents reported average annual expected rent growth to be 1.43 percentage points higher in London than in the North East, which compares to a differential of 1.78 percentage points in the simulation. From 2016 onwards, however, the model-based premium for London rises, while the survey-based premium declines. The same holds true when comparing London to the South East. One plausible explanation for this divergence between model and data is the Brexit referendum in 2016, which has had an uneven impact across England. We therefore integrate Brexit-induced demand expectations into the model, based on Whitehall projections for regional demand following Brexit. Details are described in Online Appendix D. When accounting for Brexit, the model-simulated differential rent growth expectations for the final three years align much more closely with the observed differences.

Crucially, the simulation exercise also suggests that differential relative changes in discount rates across regions cannot explain the large *cyclical swings* in price-to-rent ratio differences, such as those observed between London and the North East in Figure 2. Moreover, in the baseline scenario, our proposed mechanism accounts for 56.6% of the *level shift* in the price-

[20] This stylized fact was also documented for US superstar locations before and after the Great Financial Crisis (e.g., Kaplan *et al.* 2020, Chodorow-Reich *et al.* 2024).

to-rent ratio difference between 1997 and 2018, with the differential relative change in discount rates accounting for the remainder.[21]

3.5 Alternative Mechanisms

While our main results align with our proposed mechanism, several alternative explanations are also conceivable. We explore these one by one below and report additional results in Online Appendix C.

Segmented Markets and Local Trends in Income Inequality

To the extent that owner-occupied and rental markets are segmented and local income inequality rises cyclically over time, this could explain the rising and cyclical nature of the price-to-rent ratio. Moreover, if income inequality has risen more sharply in London than in other locations, this may account for the more pronounced increase in the capital's price-to-rent ratio.

To explore this potential alternative mechanism and control for it, we draw on detailed annual income data at the LPA level. We calculate the income dispersion as the log difference between the 8th and the 2nd decile of the local distribution of male full-time earnings at workplace. Figure C1 displays the averages for England, London, the North East, and the South East over our sample period. We include the South East here as it is similarly unaffordable to London and has very tight land use restrictions. There is no evidence of divergence between London and the North East compared to England as a whole or the South East, suggesting that differential trends in income inequality are unlikely to explain the divergence in price-to-rent ratios.

To test this conjecture more rigorously, we add the change in local income inequality as a control to the baseline regression in columns (1) to (4) of Table C2. We use two different measures of local income inequality and also run regressions that include an interaction between the change in local income inequality and the supply price elasticity. This has little impact on the coefficients of ΔLLD_t and its interaction with the supply price elasticity.

Finally, we replace the price variable in the calculation of the price-to-rent ratio with the average price for apartments, rather than using both single-family units and apartments. Apartments are more likely to be renter-occupied. Moreover, the bulk of rental properties in England is owned by private landlords, with these properties often being the owner's previous home. Therefore, when focusing solely on apartment units, we would expect rental and owner-occupied units to be much closer substitutes. The results in column (5) of Table C2 are robust to this change, suggesting that prices in the different market segments closely co-move.

Financing Costs, Land Value Share and Structure Depreciation, and Idiosyncratic Risk

To the extent that financing costs affect homeowners more strongly than landlords, lower financing costs will increase demand for owner-occupied housing relative to renting. If housing supply is relatively price inelastic, this shift in demand could lead to rising prices relative to rents. In our empirical setting, the impact of such macro-level changes in financing costs are

[21] In the Brexit scenario, differential regional demand expectations explain 54.9% of the level shift in the price-to-rent ratio difference between 1997 and 2018, of which 9.3 percentage points are attributable to the Brexit referendum.

captured by the year fixed effects. However, because housing supply constraints vary significantly across England, a given change in demand for owner-occupied housing relative to renting may differentially affect the local price-to-rent ratio. A related concern is that unobserved shocks to the relative financing cost of residential real estate could be correlated with the common component of ΔLLD_t.[22] This correlation could upwardly bias our estimated coefficients of interest.

To address these concerns, in column (1) of Table C3, we extend our baseline specification by adding the change in the real rate of mortgage interest interacted with the instrumented supply price elasticity, as an additional control. In column (2), we repeat this exercise using the change in the mortgage interest rate spread (i.e., the difference between the mortgage interest rate and the sight deposit rate) instead.[23]

Our main results are only marginally affected when we add these controls. The estimates indicate that the interactions of the supply price elasticity with the real mortgage interest rate and the mortgage interest rate spread are quantitatively less important than those with ΔLLD_t. Comparing two locations that differ in their supply price elasticity by one standard deviation, a one standard deviation decrease in the mortgage interest rate (1.23 percentage points) increases the difference in the price-to-rent ratio by 0.50 (1.23 × 0.407). In contrast, a one standard deviation higher ΔLLD_t (0.011) increases the difference by 0.70 (0.011 × 63.8).

Another related threat to identification arises from the dual nature of housing, which consists of both structure and land. While structure depreciates, land does not, resulting in a higher discount rate for structure than for land. This distinction is particularly relevant in economically thriving and supply constrained cities like London, where the land value share is significantly higher than in less flourishing places. A higher land value share implies a lower long-term discount rate and changes over time in a location's long-term discount rate may vary depending on the land value share. This suggests that given changes in the aggregate long-term real interest rate may differentially affect the price-to-rent ratio depending on a location's land value share.[24] If effective local changes in the long-term real interest rate correlate with ΔLLD_t, this could bias our estimated coefficients of interest. To address this, in column (3), we interact the (standardized) land value share by LPA in the year 2000 with the change in the long-term real interest rate.[25] The estimated coefficient is positive and significant. However, our main findings are remarkably robust to this control.[26]

[22] Financing conditions may also change due to alterations in credit availability, which could correlate with ΔLLD_t. We consider this concern in Section 3.6.

[23] We use the Bank of England's quoted mortgage interest rate, adjusted for inflation using the RPIX. During our sample period, the real mortgage rate ranges from -1.22% to 6.02%, and the spread ranges from 3.13% to 4.85%.

[24] Amaral *et al.* (2024) argue, in a similar vein, that a uniform decline in real risk-free interest rates can have heterogeneous spatial effects on house values. Falling rates may disproportionally push up prices in large agglomerations with initially high price-to-rent ratios (and high land value shares).

[25] We use the long-term rate from the Bank of England's 'A Millennium of Macroeconomic Data' compendium, updated to 2018. To construct the land value share, we make use of data on land value per hectare in 2000 – the first year with available data – published by the Valuation Office Agency. We assume an average plot size of 100m² and divide the resulting land price by the price of an average home in 2000.

[26] When we instrument for the land value share using the historic population density in 1911, the results are unchanged, except that the coefficient of the long-term interest rate interacted with the land value share becomes negative and insignificant. Repeating this exercise with the long-term real interest rate interacted with the

Finally, ΔLLD_t could correlate with changes in local risk premia, which may vary over time, for example, due to changes in market liquidity. To investigate the importance of changing local risk premia in our setting, we construct a measure of local idiosyncratic price risk at the LPA-year level, using repeated sales data from the Land Registry (1995-2018), closely following the methodology outlined in Giacoletti (2021).[27] In addition, we construct an alternative measure based on repeated sales and residual price variation after controlling for housing unit and year fixed effects. Both methodologies are detailed in Online Appendix B.

The correlations between ΔLLD_t and the idiosyncratic risk measures are very low: 0.027 for the Giacoletti (2021) measure and 0.088 for the fixed effects-based measure. This strongly suggests that within-LPA variation in idiosyncratic risk cannot account for our baseline results, which are driven by within-LPA variation in ΔLLD_t. When adding idiosyncratic risk as a control to the baseline regression in columns (4) and (5) of Table C3, the coefficients of the supply price elasticity interaction remain very stable.[28]

Relaxation of Financial Constraints Due to Positive Income Shocks

A positive shock to income may increase prices more strongly than rents to the extent that it relaxes financial constraints. Moreover, higher prices may alleviate borrowing constraints among homeowners who refinance (Cloyne *et al.* 2019). In both cases, we would expect prices and rents to increase and remain elevated but stable in the years following a demand shock even if demand changes were not autocorrelated. Our proposed mechanism instead suggests that especially in markets with inelastic supply, rents continue to increase in the years following the initial demand shock. We test this conjecture directly by regressing the changes from $t = -1$ to $t = 0,1,2,3$ (i.e., over horizons of 1 to 4 years) in prices and rents, respectively, on the contemporaneous demand change (from $t = -1$ to $t = 0$) and its interaction with the supply price elasticity. Figure C2 displays the coefficients of the demand change and its interaction with the supply price elasticity for prices in Panels A and B and for rents in Panels C and D. The coefficients from the price regressions remain fairly stable, whereas the coefficients of the rent regressions become larger in magnitude over longer horizons. This pattern is in line with our proposed mechanism.

Changes in Local Credit Availability

Another potential concern is that shocks to local credit availability, rather than our proposed mechanism, might differentially influence demand for owner-occupied versus renter-occupied housing and therefore the price-to-rent ratio. Although our Bartik measure relies solely on national industry-level growth rates, it is possible that LPAs with a high concentration of banking and real estate services industries were more exposed to shocks to national or local credit availability during our sample period. To address this, in Table C4 we replace the original labor demand measure with an adjusted version that excludes the banking and real estate

(instrumented) supply elasticity instead, also leaves our main findings unaffected. The latter interaction captures any variable that could be correlated with the local supply elasticity, not just land value shares.

[27] Our baseline results are robust to using a repeated sales-based house price index instead of the constant-composition house price index.

[28] In column (4), the coefficient of the Giacoletti (2021) risk measure is positive and significant. The counterintuitive sign may mirror the timing problem discussed in Online Appendix B. Both risk measures are negatively correlated with the price-to-rent ratio across LPAs, consistent with findings of Amaral *et al.* (2025).

services industries from the construction of the shift-share measure. The results suggest that shocks to these industries do not drive our findings.

Deregulation of Credit Markets

Relatedly, the deregulation of credit markets may account for changes in the price-to-rent ratio over time. However, in the UK, the most significant changes relating to housing credit ensued between 1983 and 1997, before the start of our sample period and well before similar changes in the US. The most important reform step, the Finance Act of 1983 abolished the interest rate cartel of the so-called 'building societies', enabling competition in the mortgage banking sector. Deregulation, therefore, does not appear to explain the growth in real house prices or the price-to-rent ratio in England since 1997.[29] Similarly, the cyclical patterns we observe are difficult to reconcile with a narrative of sustained improvements in financing conditions over time due to innovation. If the rise in the price-to-rent ratio prior to the Great Financial Crisis in England were driven by an expansion of credit supply, we would expect to see a fall in rents and rent expectations, an outcome inconsistent with the results in Tables 1 and 3. Moreover, as shown in Figure 5, our findings hold for the sub-periods 1997 to 2007 and 2008 to 2018 – that is, both before and after the Great Financial Crisis. Notably, from 2007 to 2009, the price-to-rent ratio declined significantly despite decreases in both the real mortgage interest rate and the long-term interest rate.

Rent Stickiness in Existing Contracts

In our main analysis, we use surveyed rents from both movers and stayers. These rents may be stickier than those measured through online listings for vacant rental units or from mover households alone. In institutional settings with tenancy rent control, such measures can underestimate rent increases during housing booms. Comparable rules do not exist in the English rental market, where landlords can offer new rental contracts to tenants annually. Nonetheless, landlords may hesitate to raise rents, even amid rising local housing demand.[30] Over a longer horizon, this behavior should diminish. As more tenants move and the gap to the market rent widens, adjustments should become more likely. To examine this, we run regressions using three- and five-year differences in Table C5. The results are consistent with the baseline findings, suggesting that rent stickiness in existing contracts may not be a significant factor in England, given the institutional setting.

Global Investor Demand for Second Homes in London

Finally, we examine the hypothesis that global investor demand for second homes in London or other London-specific shocks may explain the relative increase of the price-to-rent ratio in

[29] Recent work in the UK has instead focused on the persistent decline in real interest rates over the last two decades and the tightening of credit conditions in 2008. Miles and Monro (2021) argue that the surge in aggregate house prices in the UK between 1985 and 2018 was driven by increasing incomes and an unexpected fall in the real interest rate, with both components being equally important. They do not consider the role of the local housing supply price elasticity or the determinants of the price-to-rent ratio.

[30] In a setting without rent control, the relative bargaining power depends on the landlord's costs to fill a vacancy and on the tenant's moving costs (including the costs of renting another housing unit). In markets with increasing housing demand, it seems likely that the vacancy risk is relatively low, whereas moving and search costs for the tenant may be substantial due to competition from other renters. This suggests that rent adjustments during a tenancy should be common during house price booms.

London over the sample period. The difference between the predicted and actual price-to-rent ratios (i.e., the residuals) for Greater London put an upper bound to the quantitative importance of these channels. The residuals should capture the combined impact of all other factors orthogonal to ΔLLD_t. Using the baseline model, we derive predicted changes in price-to-rent ratios and calculate the predicted evolution of the price-to-rent ratio since 1997.

Panel A of Figure C3 conveys that global ('out-of-town') investor demand can explain only very little of the substantial increase in London's price-to-rent ratio since 1997. From 1997 to 2003, the average residual in London was positive but near zero. It turned negative between 2004 and 2014, but returned to near zero from 2010 onwards. Overall, the net impact of other London-specific factors appears to be minimal.[31]

Panels B to D display analogous graphs for the South East (another region with a white-collar, service-oriented workforce and tightly-constrained housing supply), the North East, and England as a whole. In all cases, the predicted and actual price-to-rent ratios align reasonably well, suggesting that region-specific global investor demand or other region-specific factors have not been major drivers of the regional divergence in the price-to-rent ratios since 1997.

3.6 Robustness Checks

In this section, we address several empirical concerns and test the robustness of our baseline results. We report results in Online Appendix C.

Selection of Instrumental Variables

First, we investigate whether the estimated coefficients of interest are sensitive to the choice of instrumental variables used to identify regulatory restrictiveness, a key component of the supply price elasticity. Our baseline specification, shown in column (5) of Table 2, employs three instrumental variables jointly. Table C6 reports results for six alternative specifications: the first three columns exclude one instrument at a time, while columns (4) to (6) include only one instrument in each case. The coefficients of interest remain very stable across all six specifications. Although the Sanderson-Windmeijer F-statistic is slightly lower in some cases, it remains sufficiently strong to indicate that weak identification is not a concern.

Sample Restrictions

Another potential concern is that excluding the nine LPAs with particularly high rent levels might affect our results. To address this, we test whether our findings are robust to an alternative approach for selecting LPAs where PRP rents serve as a reliable proxy for market rents. Instead of excluding high-rent LPAs, we restrict the sample to LPAs where the correlation between changes in PRP rents and market rents within each LPA is sufficiently strong. Figure C4 depicts a kernel density plot of the correlation between the LPA-level changes in PRP rents and market rents. While most LPAs exhibit positive or strongly positive correlations, a few display weak or even negative correlations.

[31] This does not rule out the possibility that global investor demand for second homes significantly drives local house prices in specific market segments, such as the prime market in central London (Badarinza and Ramadorai 2018) or in Manhattan in New York City (Favilukis and Van Nieuwerburgh 2021). However, in London, these prime markets or neighborhoods are too small to have a substantial impact on price trends across the entire Greater London region.

In Table C7, we restrict the sample based on the distribution displayed in Figure C4. A natural threshold is zero, and we test two additional thresholds corresponding to the local minima of the density graph at 0.1 and 0.45. For each threshold, we restrict the sample to LPAs with correlations above the threshold, as shown in columns (1) to (3). The interaction coefficients are somewhat larger than in the baseline specification, while the independent effect of ΔLLD is insignificant but of similar magnitude.

Price-to-Rent Ratio in Logs

If shocks to housing demand or the discount rate cause a proportional decrease in the local price-to-rent ratio, the decrease in absolute value would be mechanically larger in locations with tight supply constraints, such as London, simply because the level of the price-to-rent ratio is usually higher in such locations (Amaral *et al.* 2024). In column (1) of Table C8, we replicate the baseline specification from column (5) of Table 2 with the change in the log price-to-rent ratio as outcome, which addresses this concern.[32] The results clearly show a disproportionally larger impact of ΔLLD_t in supply-inelastic locations.

Price-to-Rent Ratio Based on Market Rents

We rely on PRP rents primarily because they allow us to extend the study period to 22 years, encompassing nearly two full local housing market cycles. While the correlation between log PRP rents and log market rents is very strong at 0.86, as illustrated in Figure 3, our full sample of LPAs includes several high-end market outliers where this relationship is somewhat weaker. A potential concern here is that the PRP rental data may not fully capture the behavior of market rents. To address this concern, we recalculate the price-to-rent ratio using market rents instead of PRP rents. PRP rents are lower than market rents. Thus, in order to make the regressions comparable across the different rent measures, we again use specifications in logs.

Our main results based on PRP rents are robust to restricting the sample period to the years 2010-2018, when market rents are available (see column (2) of Table C8). In column (3), we calculate the price-to-rent ratio using market rents instead of PRP rents. The coefficients of interest are remarkably robust to this change. Overall, these findings strongly indicate that PRP rent dynamics closely mirror market rent dynamics, at least within the scope of this analysis.

Results For the Full Sample of LPAs

Using market rents also allows us to revisit the sample restriction in our baseline specification, which excludes nine LPAs with particularly high rent levels. Including all LPAs in column (4) of Table C8 results in both coefficients of main interest becoming slightly larger in magnitude compared to column (3). This finding suggests that the baseline results hold also for the full sample of LPAs.

Changes in Local Labor Demand: A Placebo Test

A final concern is that the initial industry composition used to construct the shift-share measure could correlate with unobserved shocks to the relative attractiveness of renting versus owning. This concern arises from interpreting the shift-share measure as a weighted sum of generalized

[32] The log price-to-rent ratio has a less straightforward interpretation. We therefore use the price-to-rent ratio in levels for our main analysis.

difference-in-differences estimators, where each estimator builds on a comparison of initial employment shares in a particular industry (Goldsmith-Pinkham *et al.* 2020). Endogeneity concerns arise if changes in unobserved confounders are correlated with the initial industry composition. While our setting differs from that in Goldsmith-Pinkham *et al.* (2020) – notably because the impact of ΔLLD_t in our study is heterogeneous across space and over time, and the industry shares predate our sample period by 16 years – we can still assess the extent to which our results depend solely on the initial industry composition. Importantly, exogeneity of the industry composition is a sufficient condition for the exogeneity of the shift-share measure (Borusyak *et al.* 2022).

With endogenous initial industry shares, the regression coefficients could be significant even when creating the shift-share measure from any other set of serially correlated time series. To test this, we recreate the shift-share measure using simulated employment series for the 57 industries. We assume that the national-level time series are autocorrelated processes of order p and we select p by the Akaike information criterion. This yields $p = 2$ for four industries and $p = 1$ for the remaining 53. Using these simulated time series, we construct the shift-share measure based on the actual local industry composition, resulting in a placebo ΔLLD_t measure. We then estimate the baseline model with this placebo measure, repeating the entire exercise 2,000 times to obtain a parameter distribution for each regression coefficient in the baseline model. If the initial industry composition is exogenous, we expect these distributions to center around zero, with the baseline estimates located in the tails of the distributions.

Panel A of Figure C5 displays the coefficient distribution for the supply price elasticity interaction with ΔLLD_t. The estimated baseline coefficient lies outside the simulated coefficient distribution, alleviating the concern of endogenous initial industry shares.

One concern with using simulated labor demand at the national level is that the persistence in demand growth may not be accurately captured. We therefore repeat the exercise described above using the observed national-level employment series instead. In each of 2,000 iterations, we randomly reassign an observed national-level series to each local industry, ensuring it is not the series corresponding to that local industry. This exercise is much more likely to produce effects resembling the estimated baseline coefficients, as national-level shocks across industries are often correlated. Despite this, as shown in Panel B of Figure C5, the baseline estimate remains in the left tail of the simulated coefficient density.

4 Quantitative Importance of the Local Supply Price Elasticity

To assess the quantitative importance of the local supply price elasticity in the mechanism we uncover, we first decompose the predicted evolution of the price-to-rent ratio over time into its aggregate (macro) component and its local component, i.e., the impact of ΔLLD_t interacted with the supply price elasticity. Second, we conduct a counterfactual analysis, comparing the predicted price-to-rent ratios in selected regions – London, the South East and the North East – to those in two hypothetical locations: one with an average supply price elasticity and another with elastic supply at the 95th percentile.

4.1 Decomposition into Aggregate and Local Components

In Panel A of Figure 6, we use the coefficients from the baseline specification in column (5) of Table 2 to decompose the predicted price-to-rent ratio in Greater London (blue dashed line), which includes 32 LPAs, into two components: (i) the aggregate component (year fixed effects and impact of Help-to-Buy; red dashed line) and (ii) the local effects of ΔLLD_t interacted with the supply price elasticity (represented by the difference between the red and blue dashed lines). The panel also shows the actual price-to-rent ratio (solid black line). We focus on Greater London because it experienced a strong increase in demand and has severely constrained housing supply, primarily due to a high share of developed land.

Panel B shows the corresponding log labor demand measure, indexed to 1997. Dark shading highlights years when all LPAs of Greater London experienced decreasing demand, while light-grey shading indicates periods when at least one LPA faced a negative demand shock. Periods without shading represent times when demand increased across all LPAs. The general trend in London was strongly positive, fueled by the growing importance of business-oriented, financial, and other services – a more general development in superstar locations during the past decades (e.g., Eckert *et al.* 2024) – and owing to a relatively small share of employment in declining manufacturing industries, see Table B2.

The Repo/Official Bank Rate (light grey line), the real mortgage interest rate (dashed red line), and the real long-term interest rate (short-dashed blue line) are illustrated in Panel C.[33] Falling real interest rates are a potential contributor to the year fixed effects and offer a plausible explanation for the rising aggregate price-to-rent ratios observed during the sample period.

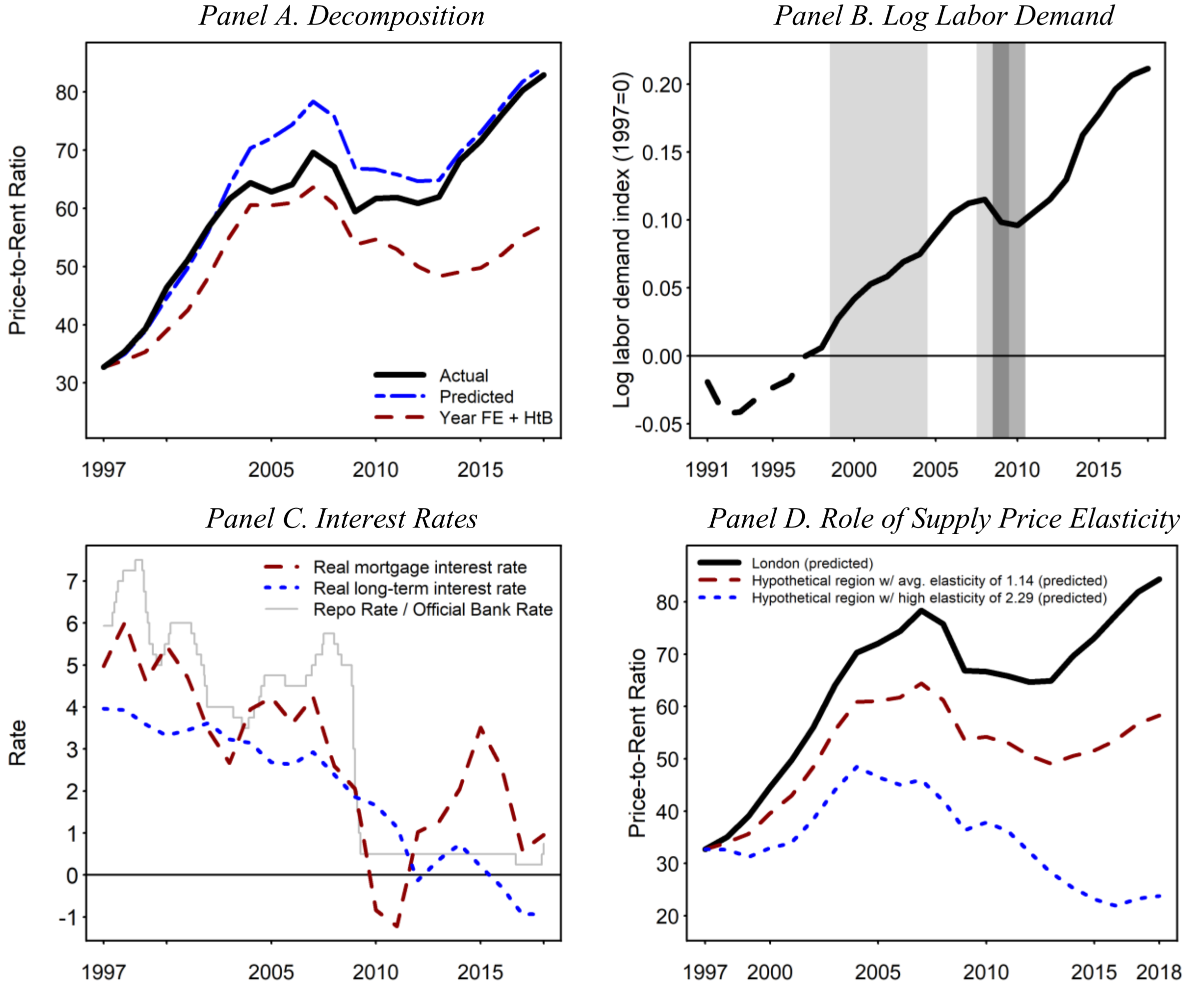
In Panel A of Figure 6, the 'unexplained component' captured by the year fixed effects increased sharply between 1997 and 2004, remained roughly stable from 2004 to 2007, then fell substantially before partially recovering between 2012 to 2018. Declining interest rates likely were a key factor explaining the rising price-to-rent ratio from 1997 to 2004, as all three reported rates dropped substantially. The time fixed effects account for 67.7% of the overall increase in the price-to-rent ratio up to the onset of the Great Financial Crisis in 2007. However, real interest rates do not appear to explain the sharp decline in the price-to-rent ratio during the Great Financial Crisis, when all three reported rates fell significantly. Similarly, the year fixed effects cannot account for the sharp rise in the price-to-rent ratio since 2009.

The interaction of ΔLLD_t and housing supply constraints in the tightly supply-constrained Greater London significantly contributed to the marked increase in the price-to-rent ratio up to 2007, resulting in a considerable gap between the red line and the blue line. The total effect of ΔLLD_t and its interaction with the supply price elasticity accounts for 32.3% of the overall increase from 1997 to 2007, when the average long-term real interest rate was 3.3%. Moreover, the interaction fully explains the increase from 2009 to 2018, when the average long-term real interest rate dropped to just 0.4%. This pattern aligns with PROPOSITION 3(iii).

[33] The Official Bank Rate was introduced in 2006 and replaced the Repo Rate in use since 1997.

Figure 6

Decomposition of the Price-to-Rent Ratio and Potential Drivers in London



Notes: Panel A displays the actual (solid black line) and predicted (dashed blue line) price-to-rent ratio, as well as the evolution of the price-to-rent ratio that is attributed to the fixed effects and Help-to-Buy (dashed red line), based on the baseline model from column (5) of Table 2. The model was used to compute LPA-level predictions, that were aggregated to the GOR of London, employing the number of households in each LPA in 2011 (Census) as weights. Panel B displays the labor demand variable indexed to 1997 and aggregated to Greater London. In years with dark shading, all LPAs experienced decreasing demand. Light-grey shading indicates periods where at least one LPA experienced decreasing demand. Demand increased in all LPAs in periods without shading. Panel C displays the Repo/Official Bank Rate (light grey line), the real mortgage interest rate (dashed red line), and the real long-term interest rate (short-dashed blue line); data source: Bank of England, '*A Millennium of Macroeconomic Data'*. Panel D compares the prediction for London (black solid line) to the prediction for a hypothetical location with an average supply price elasticity (dark-red dashed line) and a location with a supply price elasticity at the 95% quantile of the data (blue dotted line).

Overall, the decomposition strongly suggests that differential rent growth expectations, driven by persistent labor demand changes and inelastic housing supply, play a quantitatively important role in explaining price-to-rent ratio dynamics over extended periods. 52.7% of the increase in London's price-to-rent ratio from 1997 to 2018 can be attributed to ΔLLD_t and the local supply price elasticity, while the year fixed effects explain the remaining 47.3%.

This decomposition varies significantly across regions. Figure C6 reveals that in the South East – characterized by very tight regulatory constraints – the decomposition is qualitatively similar to London. However, in the North East, a region with comparably lax supply constraints, the picture is reversed. During the most recent boom period, the aggregate 'unexplained' component grew faster than both the actual and predicted price-to-rent ratios, suggesting that ΔLLD_t had a small attenuating effect on the price-to-rent ratio. This outcome is consistent with the theoretical model, which predicts that the price-to-rent ratio falls in response to a positive shock to demand in locations where housing supply is sufficiently price elastic.

4.2 Comparison of London with Hypothetical Locations

In Panel D of Figure 6, we compare Greater London to two hypothetical locations: one with an average supply price elasticity (1.14) and another with a high elasticity at the 95th percentile (2.29). Greater London and the hypothetical locations are assumed to experience the capital's ΔLLD_t.

The figure reveals substantial cyclical differences between London and the hypothetical location with average elasticity. The English planning system is amongst the strictest in the world and England's high population density further contributes to a relatively low average supply price elasticity. These factors suggest that this decomposition exercise likely understates the importance of the supply price elasticity relative to regions and countries with more elastic long-run housing supply.

When comparing London to a hypothetical location with an elasticity at the 95th percentile, the cyclical differences in the predicted price-to-rent ratios are much wider. This suggests that London's price-to-rent ratio would have declined notably over the sample period if it had the higher elasticity of this hypothetical location.

We extend this analysis in Figure C7, examining the South East in Panel A and the North East in Panel B. In the South East, the predicted price-to-rent ratio increased more steeply than in the hypothetical locations, though the difference is smaller than in London. By contrast, the North East, with below-average regulatory restrictiveness and a lower share of developed land, has a below-average supply price elasticity. As a result, the predicted price-to-rent ratio in the North East rose less sharply than in the hypothetical location with average elasticity.

5 Conclusions

The underlying causes of the housing affordability crisis are one of the most hotly contested debates amongst economists. A particularly policy-relevant question in this context is: To what extent are the rising price-to-rent ratios observed in various countries during the 2000s and 2010s – most pronounced in superstar cities such as London – consistent with housing supply shortages? A naïve view might suggest that if long-run supply constraints are important, rents should have increased just as much as prices.

In this study, we provide a novel theoretical insight. A simple mechanism; tight local supply constraints, combined with serially correlated demand changes that trigger changes in rent growth expectations, can explain several stylized facts about the price-to-rent ratio: (i) The increase in the price-to-rent ratio during the 2000s and 2010s was most pronounced in the most desirable and supply-constrained ("superstar") cities, (ii) the price-to-rent ratio fell during the same time period in markets such as Japan that experienced prolonged negative demand growth, (iii) price-to-rent ratio differences across regions are highly cyclical over the business cycle, and (iv) the spatial differences in the price-to-rent ratio are more pronounced during periods of low long-term interest rates.

Our empirical findings provide support for the proposed theoretical mechanism. They are also likely generalizable to other superstar cities and institutional contexts. London shares with many other superstar cities a very low supply price elasticity and a local industry composition dominated by business-oriented services, including finance. This implies that shocks to these industries will always trigger stronger swings in the price-to-rent ratio in superstar cities compared to their peripheral counterparts. It also implies that the cyclical patterns we uncover will likely not be confined to the 2000s and 2010s either.

Bridging mainstream urban economic and macro-finance perspectives, we highlight the critical role of local long-run supply constraints – including regulatory constraints determined in the political arena – in shaping rent growth expectations and in explaining the dramatic decline in housing affordability in superstar cities like London and other thriving locations. During economic booms, long-run supply constraints amplify both contemporaneous changes in rents and expected future rent growth, but these effects reverse during busts. This explains why in superstar cities – where the supply price elasticity is low – prices rise and fall more strongly than rents.

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Online Appendix – NOT FOR PUBLICATION

Appendix A: Theoretical derivations

A.1 Proof of PROPOSITION 3 from the main text

With $D_{t-1} = \Delta D_{t-1} = 0$, we have

$$R_t = 1 + (\gamma + \beta)e_t, \quad E_t[R_{t+j}] = 1 + \beta e_t \sum_{k=0}^{j} \rho^k.$$

The expression for prices becomes:

$$\begin{aligned}
P_t &= 1 + \frac{1}{r} + \gamma e_t + \frac{\beta e_t}{1-\rho} \sum_{j=0}^{\infty} \frac{1-\rho^{j+1}}{(1+r)^j} \\
&= 1 + \frac{1}{r} + \gamma e_t + \frac{\beta e_t}{1-\rho} \left(\frac{1}{1-\frac{1}{1+r}} - \rho \frac{1}{1-\frac{\rho}{1+r}} \right) \\
&= 1 + \frac{1}{r} + \gamma e_t + \beta e_t \frac{(1+r)(1+r-\rho-r\rho)}{r(1-\rho)(1+r-\rho)} \\
&= 1 + \frac{1}{r} + \left(\gamma + \beta \frac{(1+r)^2}{r(1+r-\rho)} \right) e_t.
\end{aligned}$$

Hence, the price-to-rent ratio is

$$\frac{P_t}{R_t} = \frac{1 + \frac{1}{r} + \left(\gamma + \beta \frac{(1+r)^2}{r(1+r-\rho)} \right) e_t}{1 + (\gamma + \beta) e_t}.$$

The derivative with respect to e_t is

$$\frac{d}{de_t} \frac{P_t}{R_t} = \frac{(\gamma + \beta(1+r))\rho - \gamma(1+r)}{r(1+r-\rho)(1+(\gamma+\beta)e_t)^2}.$$

It is larger than zero if

$$(\gamma + \beta(1+r))\rho - \gamma(1+r) > 0.$$

Clearly, the left-hand side is smaller than zero for $\gamma > 0$ and $\rho = 0$, but larger than zero when γ is small and ρ and β are sufficiently large. The derivatives of the left-hand side with respect to ρ and β, and the cross derivative with respect to β and ρ are positive.

To show PROPOSITION 3, we need to show that $\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} > 0$, $\frac{d}{d\rho}\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} > 0$, and $\frac{d}{dr}\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} < 0$, provided that the shock $e_t > 0$ is close enough to zero.

We have:

$$\begin{aligned}
\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} &= \frac{\gamma e_t\big(2-\rho+r(2+\rho)\big) + (1+r)(1-e_t\beta)\rho}{r(1+r-\rho)(1+(\beta+\gamma)e_t)^3} \\
&= \frac{e_t\big(\gamma\big(2-\rho+r(2+\rho)\big) - (1+r)\beta\rho\big) + (1+r)\rho}{r(1+r-\rho)(1+(\beta+\gamma)e_t)^3}.
\end{aligned}$$

Provided that e_t is close enough to zero and $r \in (-1,1)$, this expression is positive for $\rho > 0$ and $\gamma, \beta \geq 0$. Moreover,

$$\frac{d}{d\rho}\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} = \frac{(1+r)^2(e_t(\gamma-\beta)+1)}{\mathrm{r}\,(1+\mathrm{r}-\rho)^2\left(1+\ \mathrm{e_t}(\beta\ +\ \mathrm{g})\right)^3}.$$

This expression is positive if either $\gamma \geq \beta$, or $\gamma < \beta$ and e_t close enough to zero, i.e., $0 < e_t < \frac{1}{(\beta-\gamma)}$. Finally,

$$\frac{d}{dr}\frac{d}{d\beta}\frac{d}{de_t}\frac{P_t}{R_t} = \frac{-\rho\,((1+\mathrm{r})^2-\rho)(1-\beta\mathrm{e_t})-\gamma\mathrm{e_t}(\rho^2-\rho(3-\mathrm{r})(\mathrm{r}\ +\ 1)+2(\mathrm{r}+1)^2)}{\mathrm{r}^2\,(1+\mathrm{r}-\rho)^2\left(1+\mathrm{e_t}(\beta\ +\ \mathrm{g})\right)^3}.$$

At $e_t = 0$, the numerator is $-\rho\,((1+\mathrm{r})^2-\rho)$. This is smaller than zero since $\rho < 1$. Hence, this expression is negative for e_t close enough to zero.

This shows PROPOSITION 3.

A.2 Calculation of Price Impacts Implied by Rent Regression

For the calculations in Table 5 we assume that $\log R_{t+1} = \log R_t + \rho(\log R_t - \log R_{t-1})$, so that $R_{t+1} = \left(\frac{R_t}{R_{t-1}}\right)^\rho R_t$, and hence $R_{t+j} = (R_t/R_{t-1})^{\sum_{k=1}^{j}\rho^k} R_t$. We define prices as the discounted sum of future rental incomes, $P_t = \frac{R_t}{1+r} + \sum_{j=1}^{\infty}\frac{R_{t+j}}{(1+r)^{j+1}}$. We do not use the theoretical model directly because the supply parameters β and γ are only indirectly related to the long-run supply price elasticity.

Plugging in $R_{t+j} = (R_t/R_{t-1})^{\sum_{k=1}^{j}\rho^k} R_t$, we consider the log difference in prices over time,

$$\Delta \log P_t = \Delta \log R_t + \log\left(\frac{1}{1+r} + \sum_{j=1}^{\infty}\frac{\left(\frac{R_t}{R_{t-1}}\right)^{\sum_{k=1}^{j}\rho^k}}{(1+r)^{j+1}}\right) - \log\left(\frac{1}{1+r} + \sum_{j=1}^{\infty}\frac{\left(\frac{R_{t-1}}{R_{t-2}}\right)^{\sum_{k=1}^{j}\rho^k}}{(1+r)^{j+1}}\right). \tag{A1}$$

We use equation (A1) to compute the impact of a change in rents between periods $t-1$ and t on the change in prices, under the assumption that the location is in equilibrium, i.e., $R_{t-1} = R_{t-2}$, taking demand persistence ρ and the discount factor r as given. This allows us to compare the impact of a change in log labor demand on rents in two locations: one with a long-run supply price elasticity one standard deviation below the national average, and one with an elasticity one standard deviation above the national it.

Since the impact of the resulting change in rents on log prices as given by equation (A1) depends on the size of the demand shock, we consider a 'small' demand shock of one log point (0.01). In the location with relatively inelastic supply, the resulting change in log rents equals $(0.101\ +\ 0.095) \times\ 0.01$. In the other location, it is $(0.101 -\ 0.095) \times\ 0.01$, where 0.101 and -0.095 are the coefficients reported in column (6) of Table 1.

The differential change in $\log P_t$ using equation (A1) can then be compared to the differential impact of a change in log labor demand by one log point across two locations that differ in their supply price elasticity by two standard deviations $(0.01 \times 2 \times 0.757)$ according to column (3) of Table 1.

Appendix B: Detailed Description of Data and Construction of Variables

This online appendix provides details on the various sources and computation of variables used in our empirical analysis. Tabe B1 provides summary statistics of the variables used in the empirical analysis.

Table B1

Summary Statistics

	Mean	Standard deviation			Min.	Max.
		Overall	Between	Within		
A. Local Planning Authority (LPA) Panel, 1997-2018 (N = 353, T = 22)						
Mix-adjusted real house price index (1997 = 1) [a]	1.879	0.502	0.208	0.457	0.936	4.730
Real weekly rents (PRP rents in £)	96.1	14.7	12.8	7.2	58.9	151.4
Ratio of house prices to yearly PRP rents	50.7	22.5	19.4	11.5	15.2	327.1
Ratio of apartment prices to yearly PRP rents	33.1	16.9	14.4	9.0	5.9	243.2
Log local labor demand [b]	10.45	0.76	0.75	0.05	8.41	13.35
B. First Differences for LPA Panel, 1997-2018 (N = 353, T = 22),						
ΔLog mix-adjusted real house price index [a]	0.037	0.076	0.011	0.075	-0.213	0.396
ΔLog real weekly rents (PRP rents in £)	0.006	0.036	0.005	0.036	-0.397	0.253
ΔRatio of house prices to yearly PRP rents	1.38	4.33	0.92	4.24	-47.68	42.71
ΔRatio of apartment prices to yearly PRP rents	0.88	4.39	0.79	4.32	-68.22	68.10
ΔLog local labor demand [b]	0.008	0.011	0.003	0.010	-0.043	0.069
C. First Differences for LPA Panel, 1997-2018, harmonized/outliers removed (N = 344, T = 22)						
ΔLog mix-adjusted real house price index [a]	0.037	0.075	0.010	0.075	-0.213	0.294
ΔLog real weekly rents (PRP rents in £)	0.005	0.036	0.005	0.036	-0.397	0.253
ΔRatio of house prices to yearly PRP rents	1.29	3.98	0.59	3.93	-24.21	25.40
ΔRatio of apartment prices to yearly PRP rents	0.80	4.18	0.49	4.15	-68.22	68.10
ΔLog local labor demand [b]	0.008	0.011	0.003	0.010	-0.043	0.069
ΔIdiosyncratic house price risk (Giacoletti 2021)	0.004	0.030	0.003	0.030	-0.237	0.209
ΔIdiosyncratic house price risk (own measure)	-0.001	0.017	0.001	0.017	-0.177	0.171
D. LPA Cross Section (N = 353)						
Avg. refusal rate of major resident. projects, 1979-2018	0.242	0.082			0.065	0.473
Share of developable land developed in 1990	0.257	0.233			0.009	0.976
Range between highest and lowest altitude (in m)	209	171			5	975
Supply price elasticity	1.144	0.612			0.153	3.402
Share of greenbelt land in 1973	0.088	0.215			0.000	1.000
Change in delay rate b/w 1994–96 & 2004–06	-0.031	0.220			-0.635	0.531
Share of votes for Labour, 1983 General Election	0.163	0.091			0.001	0.410
Population density in 1911 (1 000 persons per km²)	733	2,562			3	22,029
Land value share [c]	0.114	0.077			0.029	0.982
E. Government Office Region (GOR) Panel, 2013-2018 (N = 9, T=6)						
One-year ahead expected real rent growth	-0.004	0.015	0.006	0.014	-0.041	0.033
Five-years ahead expected real rent growth	0.014	0.017	0.006	0.016	-0.018	0.051

Notes: [a] Based on house price transaction data. [b] Predicted employment, based on 1981 local industry composition and national employment growth. [c] Approximated using data on land values and house prices.

B.1 House Prices, Rents, Instrumental Variable, and Shift-Share Labor Demand Measure

House prices. We refine the house price panel of Hilber and Vermeulen (2016) and extend it from 2008 to 2018. We use the same composition adjustment as in Hilber and Vermeulen (2016) to calculate average nominal house prices by LPA and year from the Price Paid Data of the UK Land Registry. The Price Paid Data contain all property sales in England of properties sold for full market value.

For the estimation of the long-run supply price elasticity, we append the house price data using transactions recorded in the Survey of Mortgage Lenders. These data are available from 1974 to 1994. We refine the index by dropping transactions made under the Right-to-Buy scheme. The scheme allowed tenants in council housing to buy their housing units at a substantial discount. We append the full period for which the Price Paid Data are available, 1995 to 2018, to the adjusted 1974 to 1994 panel and deflate the nominal index by the RPIX.

Market rents, 2010 to 2018. The rents data are taken from the "Private Rental Market Statistics" provided by the Valuation Office Agency (VOA). The VOA conducts surveys to collect data on rents, publishing average rents separately for different housing unit types (by number of rooms) for periods of 12 months (semi-annually, in March and October). We use the March publication and assign it to the same year. As an example, the March 2015 publication covers March 2015 to February 2016, and it was assigned to the year 2015 in the panel. We follow the same aggregation strategy as for the house price index. We first calculate the average share of each housing unit type by LPA and use these shares as aggregation weights in the second step. The nominal average rent by LPA and year is the weighted sum of mean rents reported for each category in that LPA and year. We deflate the nominal rents by the RPIX.

Private Registered Provider rents, 1997 to 2018. The uk.gov Table 704 of the UK Housing Statistics reports mean rents charged by Private Registered Providers (PRP), by year (1997 to 2018), and LPA. The statistic only includes larger PRPs with more than 1,000 beds and refers to self-contained units. PRP rents are subject to a rent ceiling that is pegged to the current market rent. We deflate the nominal rents by the RPIX. For more details on the definition of the rent ceiling, see the Guidance on Rents for Social Housing, Department for Communities and Local Government (now: Ministry of Housing, Communities and Local Government), February 2019, https://www.gov.uk/government/publications/guidance-on-rents-for-social-housing.

Refusal rate. The 'refusal rate' is the number of refused 'major applications' (i.e., applications of projects consisting of ten or more housing units) divided by the total number of such applications in a given year. This is the standard measure used in the literature to capture regulatory restrictiveness in Britain – see Hilber and Vermeulen (2016).

Share of greenbelt land in 1973. One of our instruments for the average refusal rate is the share of greenbelt land in 1973. In order to construct the variable, we digitized a map of recreational land in Great Britain (Lawrence 1973). The map provides information on greenbelts designated prior to 1973. We match the map with LPA delineations of 2001 and use geographic information software to calculate the share of designated greenbelt land in each LPA in 1973.

Shift-share labor demand measure. The shares for the shift-share labor demand measure are based on data from the 1981 Census capturing the local industry composition at the 4-digit level of the 1980 Standard Industrial Classification (SIC). We combine the shares with annual data on the seasonally-adjusted number of workforce jobs in 19 industries (SIC 2007) at the national level provided by the Office for National Statistics (1978-2018). To integrate the two datasets, we map both classifications to the 57 divisions of the SIC 1992, using appropriate apportionment weights for the required mappings.[34] We exclude the construction sector because shocks to the construction industry may directly affect house prices and rents. For LPA i and year t, the shift-share measure of local labor demand is defined as $LLD_{it} = \log \sum_{k=1}^{56} emp_{i,1981}^{k} \times index_t^k$, where $emp_{i,1981}^{k}$ is employment in industry k in 1981, and $index_t^k$ is the national-level employment index for industry k in year t.

Table B2 displays the employment shares aggregated to SIC 1992 sections for England and the Government Office Regions of London, the South East, and the North East. London has a considerably lower share of manufacturing (D) but a higher share of business service activities (I, K) and employment in the financial industry (J) than England or the North East.

Table B2

Employment Shares by Industry Section in 1981

Industry Section (SIC 1992)	England	London	South East	North East
A, B Agriculture, Hunting, Forestry, Fishing	0.019	0.002	0.026	0.010
C Mining and Quarrying	0.016	0.003	0.004	0.047
D Manufacturing	0.319	0.218	0.275	0.329
E Electricity, Gas, Water Supply	0.016	0.013	0.017	0.018
F Construction [a)]	0.037	0.037	0.036	0.040
G Wholesale and Retail Trade	0.080	0.071	0.090	0.076
H Hotels and Restaurants	0.044	0.050	0.046	0.039
I Transport, Storage, Communication	0.075	0.111	0.075	0.067
J Financial Intermediation	0.037	0.047	0.042	0.029
K Real Estate, Renting, Business Activities	0.076	0.118	0.088	0.055
L Public Administration and Defense	0.084	0.101	0.087	0.083
M Education	0.051	0.060	0.064	0.045
N Health and Social Work	0.094	0.104	0.105	0.098
O Other Service Activities	0.051	0.066	0.047	0.064

Notes: Data source is the Census 1981. Jennifer Smith's job stayer correspondence weights were used to map the 4-digit SIC 1980 employment shares to SIC 1992 divisions, see this link. The shares in the table are computed by aggregating the divisions to the sections of the SIC 1992. Sections A and B were combined because of negligibly small shares in Section "B Fishing". Section names G, L, and O abbreviated. [a)] Construction sector excluded from the shift-share labor demand measure.

B.2 Estimation of Housing Supply Price Elasticities at LPA-Level

We closely follow the methodology from Saiz (2010), who estimates long-run housing supply price elasticities that capture the change in the housing stock in response to a change in house prices over a 30-year horizon.

[34] We use Jennifer Smith's job stayer correspondence weights to map the 4-digit SIC 1980 to SIC 1992 divisions, see this link. 2007 SIC industries are mapped to SIC 1992 divisions based on weights provided by the Office for National Statistics, see this link.

We use data from the UK Census to measure the number of housing units in the stock at LPA level in 1981 and 2011. LPA-level house prices in 1981 and 2011 are based on the real house price index used in the main analysis, see Online Appendix B.1.

Following Saiz (2010), we estimate the inverse supply price elasticity by regressing the change in log house prices on the change in the log housing stock, interacted with the three time-invariant supply constraint measures (the refusal rate for major residential projects, the share of developable land already developed in 1991, and the altitude range). The excluded instrument for the change in the housing stock is ΔLLD, which represents an exogenous shifter of local housing demand. We also account for the potential endogeneity of the refusal rate and the share of developed land by instrumenting for these two variables with the instruments used in the main analysis, namely the share of greenbelt land in 1973, the change in delay rate, the vote share for the Labour party in the 1983 General Election, and the population density in 1911. Section 3.2 in the main text explains the endogeneity concerns and the rationale behind each instrument.

The estimating equation is

$$\begin{aligned}\Delta_{30}\log HP_i = {} & \alpha_0 + \alpha_1\Delta_{30}\log S_i + \alpha_2\Delta_{30}\log S_i \times \overline{refusal\ rate}_i \\ & + \alpha_3\Delta_{30}\log S_i \times \%developed_i + \alpha_4\Delta_{30}\log S_i \times altitude\ range_i + \varepsilon_i.\end{aligned}$$

$\Delta_{30} log\ HP_i$ denotes the difference of the log house price index in LPA i between 1981 and 2011, and $\log S_i$ is the log number of housing units. Table B3 shows the results.

Table B3

Linear Instrumental Variables Estimation: Inverse Supply Price Elasticities

	ΔLog house price index, 1981-2011	SW-F-statistic
ΔLog housing stock, 1981-2011 (α_1)	1.309**	16.3
	(0.643)	
ΔLog housing stock × refusal rate (α_2)	0.571***	67.8
	(0.099)	
ΔLog housing stock × %developed (α_3)	1.460***	393.9
	(0.132)	
ΔLog housing stock × altitude range (α_4)	0.571***	59.1
	(0.125)	
Intercept (α_0)	0.743***	
	(0.165)	
Observations	353	

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. The house price index is described in the main text. The housing stock is the total number of dwellings and is taken from the decennial census. The difference is computed between census years 1981 and 2011. The housing supply constraints are standardized to have mean zero and standard deviation one. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016).

Column (1) displays coefficients and standard errors, while column (2) reports the corresponding Sanderson-Windmeijer F-statistics. All four coefficients in column (1) are positive and significant, suggesting that the inverse elasticity is higher in locations where supply is more tightly constrained. Column (2) shows that the instruments are sufficiently strong. This applies in particular to the instruments that explain the spatial variation in supply constraints. Table B4 shows the corresponding first-stage regression results.

Table B4

First-Stage Results for Table B3 - Linear Instrumental Variables Estimation of Inverse Supply Price Elasticities

	(1)	(2)	(3)	(4)
Dependent Variable:	ΔLog housing stock	ΔLog housing stock × % developed	ΔLog housing stock × refusal rate	ΔLog housing stock × ruggedness
Δ*LLD*, 1981-2011	0.066	0.085	0.560***	0.028
	(0.047)	(0.094)	(0.093)	(0.114)
Δ*LLD* × share greenbelt	-0.130***	0.103***	0.175**	-0.017
	(0.022)	(0.038)	(0.069)	(0.033)
Δ*LLD* × change in delay rate	0.018	0.071	-0.117*	-0.056
	(0.038)	(0.072)	(0.062)	(0.049)
Δ*LLD* × vote share Labour, 1983	-0.079**	0.256***	-0.435***	-0.060
	(0.038)	(0.076)	(0.093)	(0.083)
Δ*LLD* × pop. density 1911	-0.046***	0.252***	-0.091***	0.086***
	(0.015)	(0.046)	(0.028)	(0.022)
Δ*LLD* × altitude range	0.039	-0.509***	-0.089	1.182***
	(0.038)	(0.120)	(0.097)	(0.176)
Intercept	0.255***	-0.056***	-0.075***	0.005
	(0.010)	(0.020)	(0.016)	(0.021)
Observations	353	353	353	353
Adj. R-squared	0.074	0.331	0.218	0.381

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. *LLD* is the log labor demand measure as described in the main text. The housing stock is the total number of dwellings and is taken from the decennial census. The difference is computed between census years 1981 and 2011.

The inverse supply constraints implied by this regression can be obtained as the combined coefficient of $\Delta_{30}\log S_i$, i.e.,

$$\hat{\beta}_i^{inv} = \hat{\alpha}_1 + \hat{\alpha}_2\overline{refusal\ rate}_i + \hat{\alpha}_3\%developed_i + \hat{\alpha}_4 altitude\ range.$$

This is problematic when $\hat{\beta}_i^{inv} < 0$, which applies to a few cases in our setting. We therefore run an alternative non-linear IV regression that constrains $\hat{\beta}_i^{inv}$ to the positive domain. Like before, we assume that the inverse supply price elasticity is a function of the supply constraints and define:

$$\Delta_{30}\log HP_i = \alpha + \beta_i^{inv}\Delta_{30}\log S_i + e_i,$$

$$\beta_i^{inv} = e^{\beta_0 + \beta_r\overline{refusal\ rate}_i + \beta_d\%developed_i + \beta_a altitude\ range_i}.$$

The parameters $\beta_0, \beta_r, \beta_d, \beta_a$ and α are estimated by nonlinear GMM-IV using the same set of instruments as in the linear IV regression. In this framework, the supply price elasticity is given by

$$\beta_i = 1/\beta_i^{inv} = e^{-\beta_0 - \beta_r\overline{refusal\ rate}_i - \beta_d\%developed_i - \beta_a altitude\ range_i}.$$

The parameter estimates for $\beta_0, \beta_r, \beta_d, \beta_a$, and α are shown in Table B5.

Table B5

Nonlinear Instrumental Variables Estimation:
Inverse Supply Price Elasticities

Dependent Variable	ΔLog house price index 1981-2011
β_0	0.038
	(0.449)
Average refusal rate (β_r)	0.422**
	(0.194)
%Developed (β_d)	0.708***
	(0.165)
Altitude range (β_a)	0.279***
	(0.087)
Intercept (α)	0.712***
	(0.104)
Observations	353

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The estimated inverse supply price elasticities from the linear and nonlinear IV approaches exhibit a correlation of .923 and are hence very similar. With respect to the main empirical analysis, this implies that the cross-sectional variation is also very similar.

Table B6 shows average estimated supply price elasticities for the Government Office Regions of England based on the estimated coefficients from Table B5. A file with the estimated supply price elasticity of each LPA is available from this link.

Table B6

Average Supply Price Elasticities in English Regions

Government Office Region	Elasticity
London	0.28
South East	0.92
South West	1.10
West Midlands	1.13
North West	1.16
Yorkshire and the Humber	1.34
East of England	1.46
North East	1.53
East Midlands	1.59

Notes: The table reports the average supply price elasticity in each English Government Office Region, based on the coefficient estimates reported in Table B5.

B.3 Construction of Idiosyncratic Risk Measures

In Section 3.6, we employ two time-varying measures of idiosyncratic investment risk at LPA level. We use data from the Land Registry to calculate LPA-year-level measures of idiosyncratic price risk. The first measure is based on Giacoletti (2021), who uses the concept of Local Market Equivalent, LME, defined as the abnormal performance of a house resale:

$$LME_{i,t_0,t_1} = \frac{\frac{P_{i,t_1}}{P_{i,t_0}}}{\frac{Q_{t_1}}{Q_{t_0}}} - 1 - \frac{D_{i,t_0,t_1}}{P_{i,t_0}}.$$

The numerator of the first term is one plus the capital gain of the individual house, where P_{i,t_0} and P_{i,t_1} are the sales prices of house i in years t_0 and t_1. The denominator is one plus the increase in local house prices between years t_0 and t_1, where Q_t is the local house price index. D_{t_0,t_1} are discounted maintenance expenditures. In Giacoletti (2021), this latter term does not turn out to be an important driver of idiosyncratic investment risk. Since we do not have detailed data on maintenance expenditures, we ignore this term.

Giacoletti (2021) then defines $lme_{i,t_0,t_1} = ln(1 + LME_{i,t_0,t_1})/\sqrt{t_1 - t_0}$ and runs the following regression:

$$lme_{i,t_0,t_1} = x'_{i,t_0}\beta + \psi_{postcode} + \phi_{t_1-t_0} + u_{i,t_0,t_1}.$$

Here, x'_{i,t_0} are controls including the initial purchase price P_{i,t_0}, $\psi_{postcode}$ is a postcode fixed effect, and $\phi_{t_1-t_0}$ is a holding period fixed effect. u_{i,t_0,t_1} is the residual. We run this regression separately for each LPA. Giacoletti (2021) interprets variation in u_{i,t_0,t_1} as capturing investment risk in period t_1, implicitly assuming that the initial purchase price P_{i,t_0} is exogenous, and that it captures the fundamental value of the property. The idiosyncratic volatility in year t in that LPA is given by the empirical standard deviation of $u_{i,t_0,t}\sqrt{t - t_0}$, calculated over all observations with a repeated sale in period t.

In addition, we construct an alternative, simpler measure that accounts for the fact that u_{i,t_0,t_1} potentially depends on idiosyncratic volatility in both the initial purchase period t_0 and the sale period t_1. This measure is defined via the following FE-OLS regression at property level:

$$\log P_{it} = \psi_i + \phi_t + x'_{it}\beta + u_{it}.$$

ψ_i and ϕ_t are property- and year-fixed-effects and x'_{it} are time-variant controls (in our case, this is a dummy for the property being newly constructed in period t, and a dummy for month of sale). We run this regression separately for each LPA.

Because ψ_i captures all time-invariant determinants of property i's price, ϕ_t is essentially a repeated-sales price index. We ignore unobserved changes to the property's characteristics, and changes in the valuation of the property's characteristics over time. Apart from this caveat, u_{it} captures the idiosyncratic component of the sales price in period t. We use the empirical standard deviation of u_{it}, calculated over all observations with a sale in period t as the idiosyncratic risk measure for year t in the LPA.

Appendix C: Additional Results

C.1 First-Stage Regression Results

Table C1

First-Stage Regressions Relating to Tables 1 and 2

	(1)	(2)	(3)
Models	Col. (2), (5) of Table 1	Col. (2), (5) of Table 1	Col. (3), (6) of Table 1 & Col. (1), (2) of Table 2
Endogenous variable	Refusal rate	%Developed	Elasticity
ΔLog local labor demand (ΔLLD_t)	0.134*	-0.015	-0.045
	(0.074)	(0.070)	(0.095)
ΔLLD_t × share greenbelt in 1973	0.264***	0.053**	-0.265***
	(0.044)	(0.026)	(0.042)
ΔLLD_t × change in delay rate	-0.107***	-0.031	0.128**
	(0.041)	(0.041)	(0.052)
ΔLLD_t × share Labour vote in 1983	-0.584***	0.289***	0.058
	(0.043)	(0.044)	(0.059)
ΔLLD_t × population density in 1911	0.021	0.572***	-0.509***
	(0.020)	(0.072)	(0.080)
ΔLLD_t × altitude range	-0.028	-0.351***	-0.145**
	(0.050)	(0.052)	(0.066)
Introduction of Help-to-Buy × London	0.005***	0.015***	-0.013***
	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes
Observations	7,211	7,211	7,211
Number of LPAs	344	344	344
Adj. R-squared	0.454	0.525	0.202

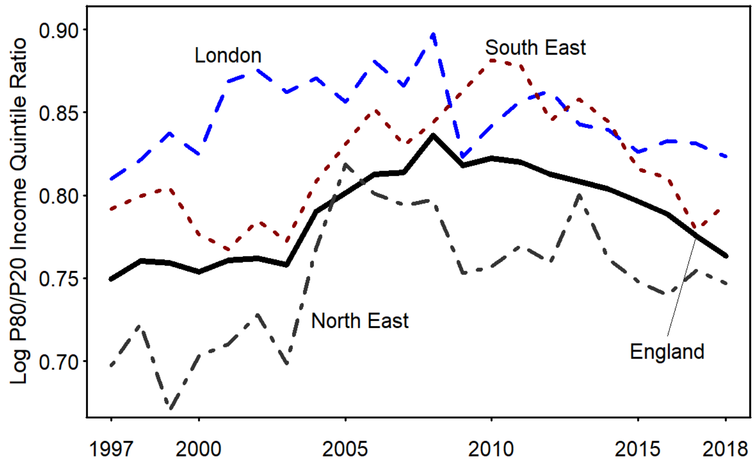
Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. The models in columns (2) and (5) of Table 1 and, respectively, in columns (3) and (6) of Table 1 and in columns (1) and (2) of Table 2 have the same first stage. In columns (1) and (2), the excluded instruments in the second stage are the share greenbelt in 1973, the change in delay rate, the share Labour vote in 1983, and population density in 1911, all interacted with ΔLLD_t. The altitude range interacted with ΔLLD_t is an included instrument in the second stage. In column (3), it is an excluded instrument in the second stage.

C.2 Alternative Mechanisms

This section shows additional empirical results to test for alternative mechanisms and the robustness of the baseline IV specification. Descriptions and a discussion of the results are found in Sections 3.5 and 3.6 in the main text.

Figure C1

Income Inequality in England, London, the South East, and the North East of England, 1997-2018



Notes: The graph displays the average log ratio of the 80% income quantile to the 20% income quantile at LPA level, aggregated to England and the GORs London, the South East, and the North East. The data source is the Annual Survey of Hours and Earnings, Table 7.1a - Weekly pay for full-time male workers at workplace.

Table C2

Local Income Inequality and Market Segmentation

	(1)	(2)	(3)	(4)	(5)
Dependent variable	ΔPrice-to-rent ratio	ΔPrice-to-rent ratio	ΔPrice-to-rent ratio	ΔPrice-to-rent ratio	ΔApartment prices-to rent ratio
Inequality measure	P80/P20	P80/P20	Gini	Gini	
ΔLLD_t	29.467**	29.634**	29.411**	29.901**	16.596
	(12.191)	(12.257)	(12.136)	(12.161)	(10.855)
ΔLLD_t × supply price elasticity	-59.391***	-60.086***	-59.231***	-59.183***	-35.670***
	(10.457)	(10.684)	(10.523)	(10.511)	(9.345)
ΔHelp to Buy dummy	-0.169	-0.170	-0.173	-0.133	0.348
	(0.595)	(0.587)	(0.591)	(0.594)	(0.485)
ΔLocal income inequality	-0.038	-0.031	-0.351	-0.425	
	(0.292)	(0.299)	(1.091)	(1.027)	
ΔLocal income inequality × supply price elasticity		0.250		-2.531	
		(0.591)		(1.539)	
Year FE	Yes	Yes	Yes	Yes	Yes
Controls for lags of ΔLLD_t	Yes	Yes	Yes	Yes	Yes
Observations	6,215	6,215	6,215	6,215	7,211
Number of LPAs	344	344	344	344	344
SW-F, ΔLLD_t × elasticity	41.6	35.3	41.7	36.0	42.2
SW-F, ΔLLD_{t-1} × elasticity	38.3	33.8	38.8	37.1	46.3
SW-F, ΔLLD_{t-2} × elasticity	28.0	31.7	28.3	26.8	40.1
SW-F, ΔLLD_{t-3} × elasticity	42.6	38.2	43.5	37.2	46.2
SW-F, Δinequality × elasticity		32.3		26.0	

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. In columns (1) and (2), local income inequality is the log difference between the 80% and the 20% quantile of the local earnings distribution. In columns (3) and (4), local income inequality is measured as the Gini coefficient, which we approximate from data on eleven quantiles across the local earnings distribution and the mean of the local distribution. Higher values of the local income inequality measure indicate greater inequality in both cases. Source: Annual Survey of Hours and Earnings, Table 7.1a - Weekly pay for full-time male workers at workplace. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016). All regressions control for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

Table C3

Mortgage Financing Conditions and Idiosyncratic Investment Risk

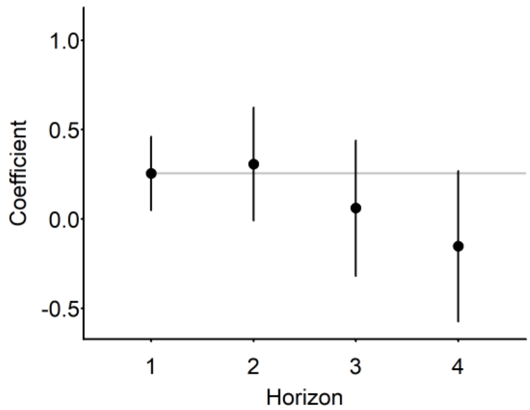
	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Price-PRP-rent ratio				
Additional controls:	ΔReal mortgage rate × elasticity	ΔMortgage rate spread × elasticity	ΔLT real rate × land value share	ΔIdiosync. risk (Giacoletti 2021)	ΔIdiosync. risk (OLS-FE residuals)
ΔLLD_t	20.072*	26.252***	23.000**	22.955**	22.796**
	(12.197)	(9.004)	(10.706)	(10.658)	(10.772)
ΔLLD_t × supply price elasticity	-63.802***	-46.398***	-60.201***	-59.821***	-60.220***
	(7.974)	(7.879)	(9.043)	(8.823)	(9.048)
ΔHelp to Buy dummy	-0.681*	-0.590	-0.421	-0.423	-0.454
	(0.357)	(0.471)	(0.372)	(0.385)	(0.387)
ΔReal mortgage rate × supply price elasticity	0.407***				
	(0.068)				
ΔMortgage rate spread × supply price elasticity		-1.526***			
		(0.394)			
ΔLong-term real interest rate × land value share			0.033		
			(0.109)		
ΔIdiosyncratic volatility (Giacoletti 2021)				7.720***	
				(1.164)	
ΔIdiosyncratic volatility (OLS-FE residual variation)					-0.477
					(1.985)
Year FE	Yes	Yes	Yes	Yes	Yes
Controls for lags of ΔLLD_t	Yes	Yes	Yes	Yes	Yes
Observations	7,211	7,211	7,211	7,211	7,211
Number of LPAs	344	344	344	344	344
SW-F, ΔLLD_t × elasticity	37.3	38.9	42.1	41.7	42.0
SW-F, ΔLLD_{t-1} × elasticity	34.3	49.3	51.2	45.2	44.5
SW-F, ΔLLD_{t-2} × elasticity	34.8	36.7	38.7	40.3	40.7
SW-F, ΔLLD_{t-3} × elasticity	43.5	53.1	47.9	46.3	46.0
SW-F, Δreal m. rate × elasticity	32.5				
SW-F, Δspread × elasticity		31.0			

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. The interactions of the supply constraints with the real mortgage interest rate in column (1) and the spread (mortgage rate minus sight deposit rate) in column (2) are instrumented by the interactions of the respective variable with the instruments discussed in Section 3.2. The idiosyncratic volatility measure in column (4) is based on Giacoletti (2021). The measure in column (5) is based on residual variation using repeated sales, see Online Appendix B. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016) (omitted for other endogenous variables). All regressions control for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

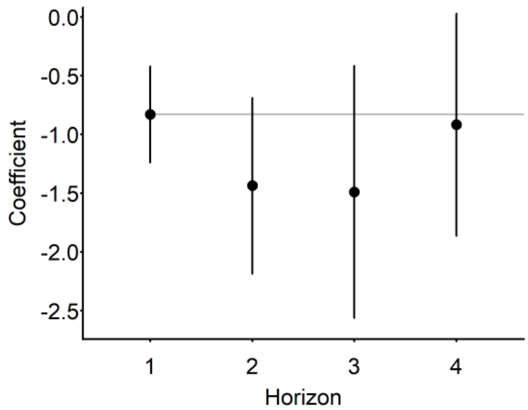
Figure C2

Impact of Demand Changes on Cumulative Change of Prices and Rents

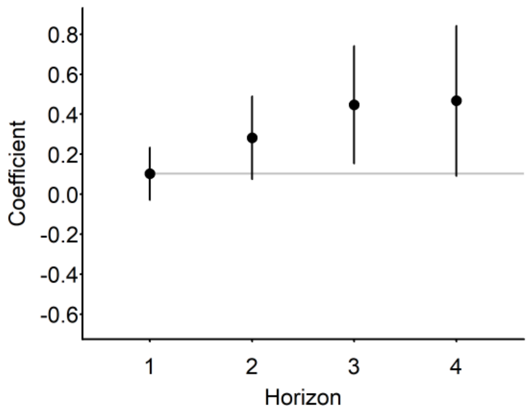
Panel A. Prices, independent effect



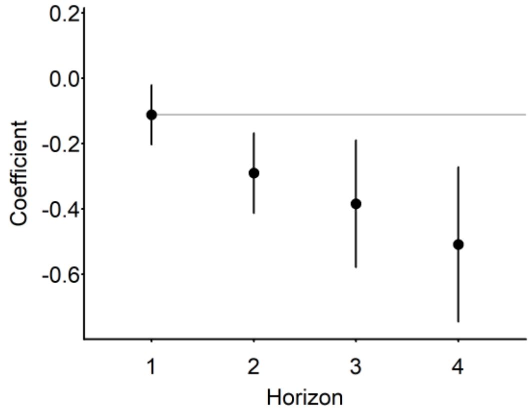
Panel B. Prices, interaction effect



Panel C. Rents, independent effect



Panel D. Rents, interaction effect



Notes: Black dots represent point estimates, with the cumulative change from $t = -1$ to $t = 0, 1, 2, 3$ as the outcome. Vertical lines show cluster-robust 95% confidence intervals. Panel A displays the coefficients for the independent effect of ΔLLD on cumulative changes in prices and Panel B displays the corresponding interaction effect (ΔLLD × supply price elasticity).. Panels C and D show the respective results for cumulative changes in rents.

Table C4

Adjusted Change in Labor Demand (w/o Banking & Real Estate Services)

	(1)
Dependent variable:	ΔPrice-to-rent ratio
ΔLLD_t(adjusted)	20.976**
	(9.888)
ΔLLD_t (adjusted) × supply price elasticity	-57.913***
	(9.116)
ΔHelp to Buy dummy	-0.582
	(0.404)
Year FE	Yes
Controls for lags of ΔLLD_t (adjusted)	Yes
Observations	7,211
Number of LPAs	344
SW-F, ΔLLD_t (adjusted) × elasticity	38.9
SW-F, ΔLLD_{t-1} (adjusted) × elasticity	38.3
SW-F, ΔLLD_{t-2} (adjusted) × elasticity	34.5
SW-F, ΔLLD_{t-3} (adjusted) × elasticity	48.1

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. The adjusted ΔLLD measure is constructed excluding financial and real estate services. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016). The regression controls for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

Table C5

Regressions Using Multi-Year Differences

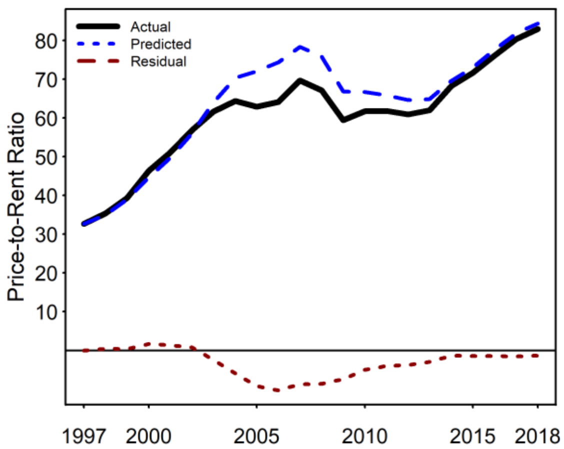
Dependent variable:	ΔPrice-to-rent ratio	
	(1)	(2)
	Differencing over three years	Differencing over five years
Δ*LLD*	21.001*	18.593
	(12.672)	(13.452)
Δ*LLD* × supply price elasticity	-73.113***	-63.572***
	(9.226)	(9.561)
ΔHelp to Buy dummy	2.380**	5.478***
	(0.965)	(1.294)
Year FE	Yes	Yes
Observations	6,523	5,835
Number of LPAs	344	344
SW-F, Δ*LLD* × elasticity	26.3	26.2

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. All regressions are in differences. The column heading indicates the number of years over which the differences are computed (3 and 5 years, respectively). The regressions also include year fixed effects to capture average national-level changes over the respective period. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016).

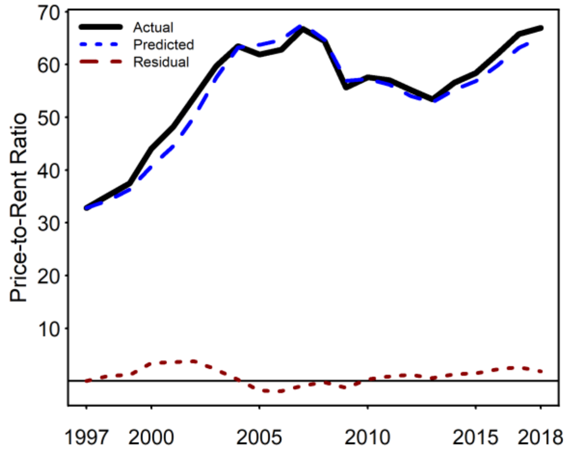
Figure C3

Actual and Predicted Price-to-Rent Ratios, and Residuals in London, the South East, the North East, and England

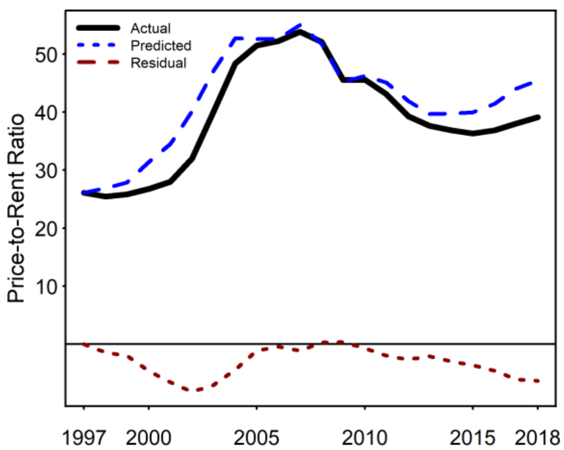
Panel A. London



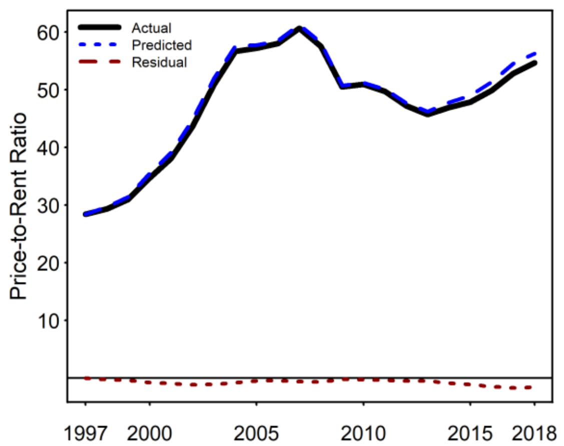
Panel B. South East



Panel C. North East



Panel D. England



Notes: The graphs display the actual price-to-rent ratio for the respective region as a black solid line, along with the model-predicted value as a blue dashed line, and the difference as a red dotted-dashed line. Predictions are based on the baseline model from column (5) of Table 2, aggregated by year to the GORs (Panels A, B, C) and to England as a whole (Panel D).

C.3 Robustness Checks

Table C6

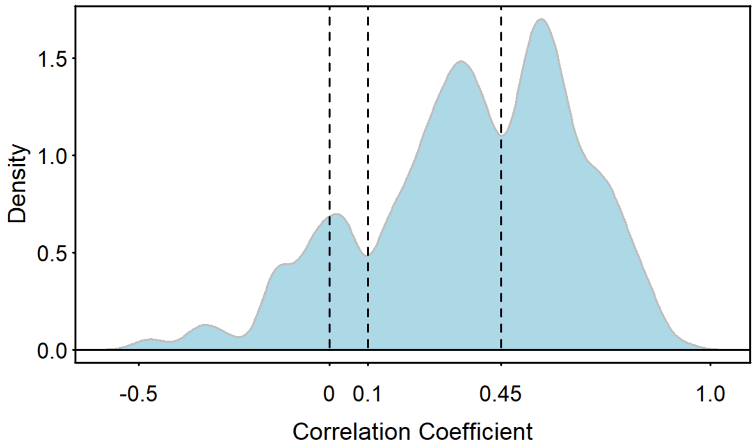
Robustness of Baseline Results to the Selection of Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding greenbelt instrument	Excluding delay rate instrument	Excluding Labour votes instrument	Only greenbelt instrument	Only delay rate instrument	Only Labour votes instrument
ΔLLD_t	18.882*	22.941**	23.232**	23.070**	19.935*	18.321*
	(10.224)	(11.201)	(10.738)	(11.003)	(10.349)	(10.795)
ΔLLD_t × supply price elasticity	-54.436***	-63.698***	-57.314***	-58.383***	-49.286***	-59.899***
	(11.666)	(9.375)	(9.466)	(10.498)	(13.338)	(12.324)
ΔHelp to Buy dummy	-0.496	-0.666*	-0.193	-0.263	0.010	-0.918***
	(0.361)	(0.365)	(0.491)	(0.551)	(0.570)	(0.323)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls for lags of ΔLLD_t	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,211	7,211	7,211	7,211	7,211	7,211
Number of LPAs	344	344	344	344	344	344
SW-F, ΔLLD_t × elasticity	41.1	52.1	50.9	70.2	52.4	46.6
SW-F, ΔLLD_{t-1} × elasticity	35.4	56.0	55.1	76.0	44.9	49.0
SW-F, ΔLLD_{t-2} × elasticity	31.1	48.9	55.6	69.0	42.4	36.5
SW-F, ΔLLD_{t-3} × elasticity	45.0	59.6	57.1	82.4	58.5	54.2

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. The specifications use different sets of instruments for the average refusal rate, which is an important determinant of the supply price elasticity. The refusal rate instruments used or excluded are denoted by the column headings. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016). All regressions control for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

Figure C4

Correlation between Changes in Market Rents and PRP Rents at LPA Level



Notes: The graph displays the distribution of the correlation between changes in market rents and PRP rents at LPA level. The dashed vertical lines indicate the three thresholds used to select the samples for Table C7 (correlation exceeding 0.0, 0.1, and 0.45).

Table C7

Robustness Checks for Selection of Rent Measure

	(1)	(2)	(3)
Dependent variable	ΔPrice-PRP rent ratio		
LPA-level correlation of changes in PRP rents and market rents	> 0	> 0.1	> 0.45
ΔLLD_t	25.994	21.836	22.719
	(17.295)	(18.820)	(24.859)
ΔLLD_t × supply price elasticity	-104.001***	-104.685***	-102.191***
	(24.254)	(24.197)	(26.508)
ΔHelp to Buy dummy	-1.971***	-1.933***	-1.295**
	(0.544)	(0.580)	(0.580)
Year FE	Yes	Yes	Yes
Controls for lags of ΔLLD_t	Yes	Yes	Yes
Observations	6,539	6,119	3,221
Number of LPAs	312	292	154
SW-F, ΔLLD_t × elasticity	39.6	36.7	23.7
SW-F, ΔLLD_{t-1} × elasticity	41.6	37.1	27.8
SW-F, ΔLLD_{t-2} × elasticity	37.9	39.1	27.1
SW-F, ΔLLD_{t-3} × elasticity	42.9	38.7	26.4

Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. Instruments include: Share of greenbelt land in 1973, change in delay rate b/w 1994–96 & 2004–06, share of votes for Labour in 1983 General Election, population density in 1911, and altitude range. Each column uses a different sub-sample, based on lower bounds for the correlation between changes in PRP rents and market rents at LPA level, as indicated in the column header. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016). All regressions control for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

Table C8

Change in Log Price-to-Rent Ratio as Dependent Variable

	(1)	(2)	(3)	(4)
Dependent variable	ΔLog price-PRP rents ratio	ΔLog price-PRP rents ratio	ΔLog price-market rents ratio	ΔLog price-market rents ratio
Sample	Baseline sample 1997-2018	Baseline sample 2010-2018	Baseline sample 2010-2018	All LPAs 2010-2018
ΔLLD_t	0.384**	1.041***	0.500**	0.698***
	(0.154)	(0.268)	(0.223)	(0.266)
ΔLLD_t × supply price elasticity	-0.775***	-1.088**	-0.697**	-0.867***
	(0.135)	(0.436)	(0.315)	(0.301)
ΔHelp to Buy dummy	0.003	0.007	0.029***	0.026***
	(0.008)	(0.014)	(0.010)	(0.008)
Year FE	Yes	Yes	Yes	Yes
Controls for lags of ΔLLD_t	Yes	Yes	Yes	Yes
Observations	7,211	3,095	2,752	2,824
Number of LPAs	344	344	344	353
SW-F, ΔLLD_t × elasticity	42.2	59.5	63.4	73.2
SW-F, ΔLLD_{t-1} × elasticity	46.3	63.9	57.9	61.4
SW-F, ΔLLD_{t-2} × elasticity	40.1	16.8	15.4	22.3
SW-F, ΔLLD_{t-3} × elasticity	46.2	58.8	56.9	64.6

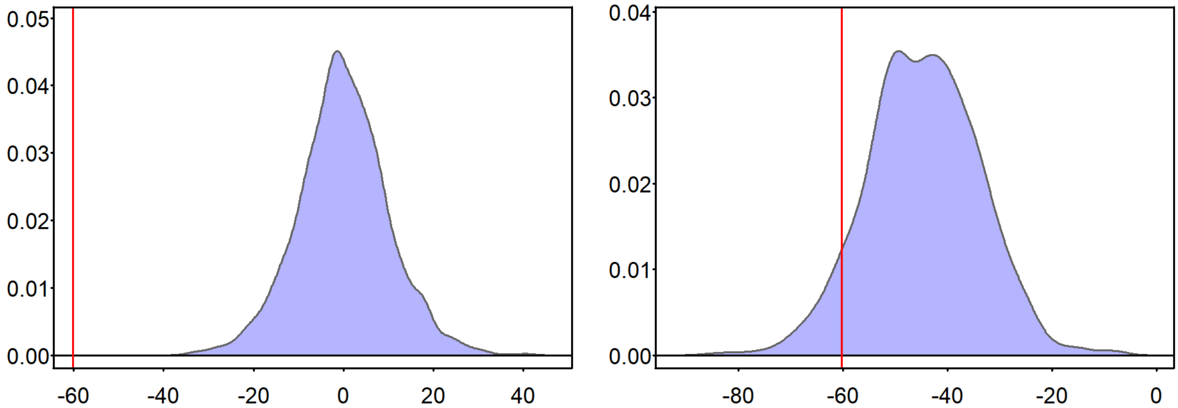
Notes: Standard errors in parentheses clustered by TTWA. *** p<0.01, ** p<0.05, * p<0.1. The excluded instruments are the share greenbelt in 1973, the change in delay rate, the share Labour vote in 1983, population density in 1911, and altitude range all interacted with ΔLLD_t. SW-F is the conditional F-statistic of Sanderson and Windmeijer (2016). All regressions control for three lags of ΔLLD_t and its interactions with the supply price elasticity, as in the baseline regression (column (5) of Table 2).

Figure C5

Placebo Tests: Simulated Densities for the Baseline Regression Interaction Effect of the Change in Log Labor Demand and the Supply Price Elasticity

Panel A. Artificial industry-level employment growth

Panel B. Random assignment of national-level employment growth to industry shares

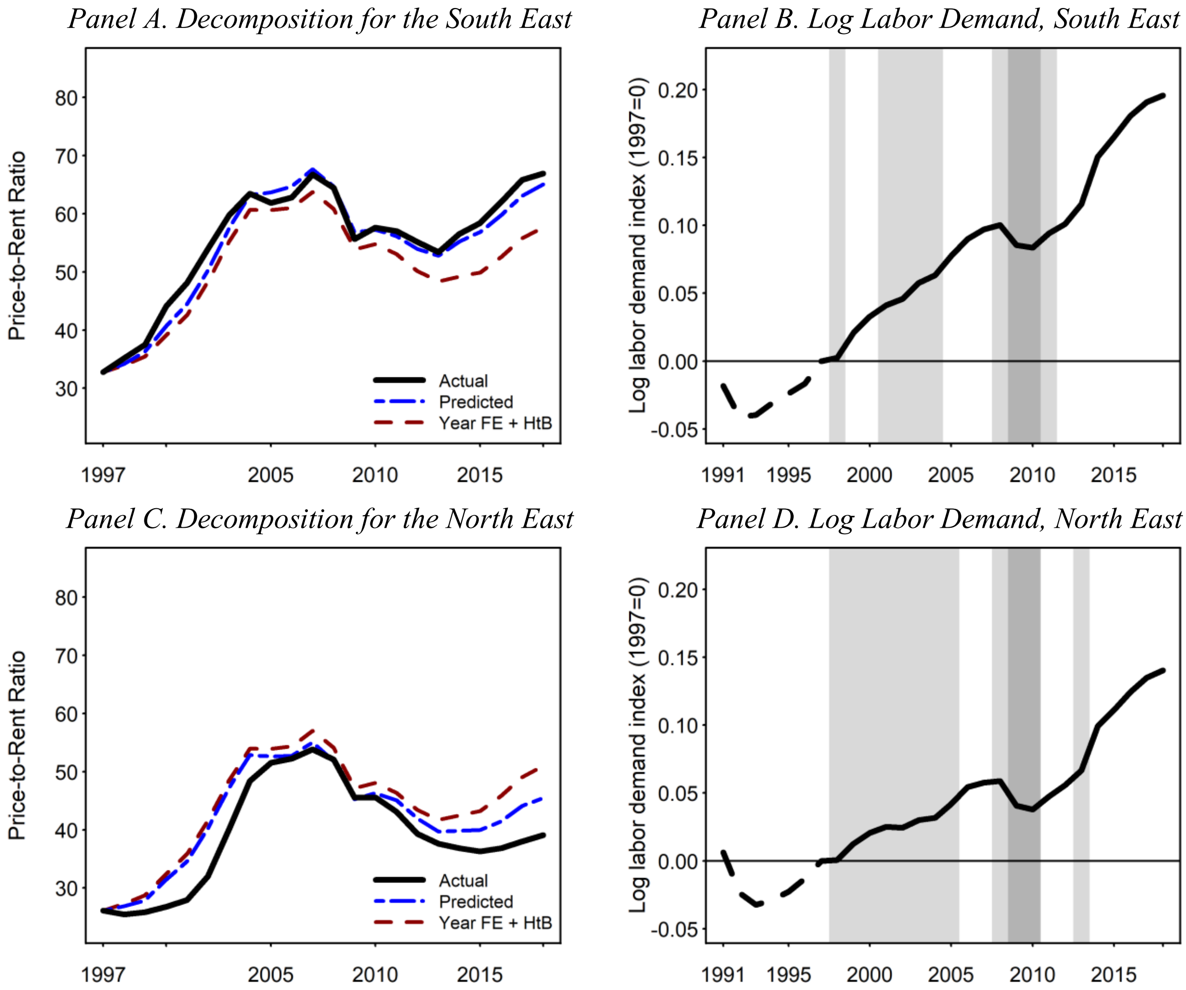


Notes: The graphs are based on the model displayed in column (5) of Table 2. The graphs display the coefficient distributions from 2,000 repetitions. Panel A shows the interaction effect when using simulated placebo ΔLLD measures instead of the original ΔLLD. Panel B uses a placebo ΔLLD measure based on random assignment of observed industry-level employment growth to local industries. The red vertical line represents the baseline coefficient estimate.

C.4 Quantitative Analysis

Figure C6

Decomposition of the Price-to-Rent Ratio and Log Labor Demand in the South East and the North East of England



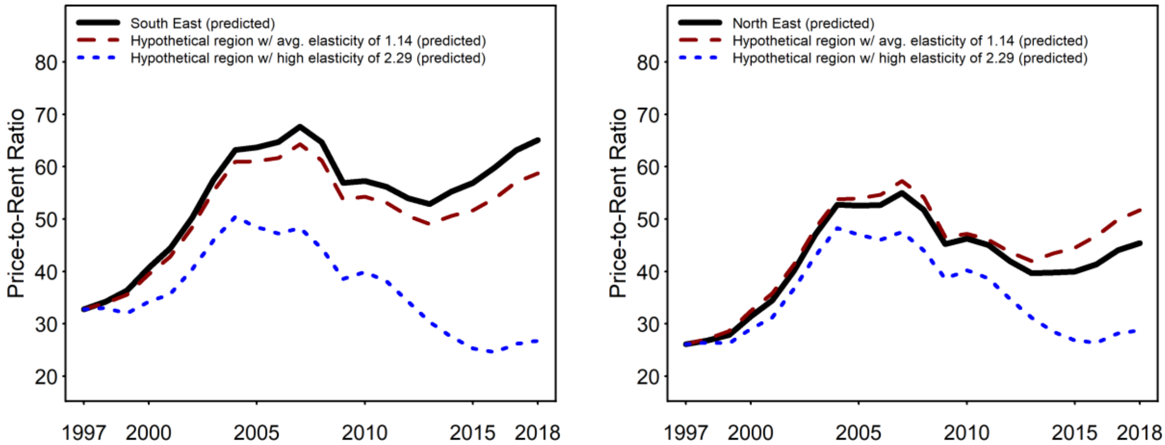
Notes: Panels A and C display the actual (solid black line) and predicted (dashed blue line) price-to-rent ratio, as well as the evolution of the price-to-rent ratio that is attributed to the fixed effects and Help-to-Buy (dashed red line), based on the model in column (5) of Table 2, aggregated to the GORs South East and North East of England, respectively, employing the number of households in each LPA in 2011 (Census) as weights. Panels B and D display the corresponding labor demand variable indexed to 1997. In years with dark shading, all LPAs experienced decreasing demand. Medium-grey shading indicates periods with more than 50%, but less than 100% of LPAs experiencing decreasing demand. Light-grey shading represents periods with less than 50%, but more than 0% LPAs with decreasing demand. In periods without shading, demand increased in all LPAs.

Figure C7

Counterfactual Decomposition Relative to a Location with Average Elasticity and a Location with High Elasticity at 95th Percentile

Panel A. Comparison of the South East to Hypothetical Locations

Panel B. Comparison of the North East to Hypothetical Locations



Notes: All graphs are based on the model displayed in column (5) of Table 2. The model was used to compute LPA-level predicted changes that were aggregated to GORs, employing the number of households in each LPA in 2011 (Census) as weights. Values in 1997 represent the level of the price-to-rent ratio as observed in the data. The dark-red dashed lines show the predictions for a hypothetical location with an average supply price elasticity. The blue dotted lines show the predictions for a hypothetical location with relatively elastic housing supply (95th percentile). In each panel, the evolution of labor demand reflects the observed labor demand changes in the respective region (South East and North East).

Appendix D: Model Simulations

D.1 Baseline Model

We use the theoretical model to conduct simulations. For the simulation exercise, we redefine the demand process and the relationship between rents and demand changes as follows:

$$\log D_t = \log D_{t-1} + \rho \Delta \log D_{t-1} + e_t,$$

$$\log R_t = \beta \log D_t + \gamma e_t,$$

$$E_t[\log R_{t+j}] = \beta \log D_t + \beta \Delta \log D_t \sum_{k=1}^{j} \rho^k, \ \ j > 0.$$

This reformulation has the benefit that the magnitude of shocks can be interpreted as log points and hence the simulation does not depend on initial levels of prices and rents.[35]

Moreover, we employ arguably plausible assumptions informed by the data about discount rates, persistence in rent growth expectations, and location-specific parameters capturing long- and short-run supply constraints. In doing so, we allow for level differences in local discount rates across locations that reflect differences in risk (Amaral *et al.* 2025), and the secular trend in real interest rates depicted in Panel C of Figure 6. We then infer shocks to housing demand e_t in each location so that the model-derived evolution of the price-to-rent ratio matches the observed evolution in each location.

We select three locations, London, the South East, and the North East. London is England's superstar city and is characterized by very high house prices and a very low supply price elasticity. The South East is the region with the second-highest house prices and it exhibits very tight regulatory constraints to housing supply. The North East is the region with the lowest level of house prices and the laxest regulatory constraints in England.

This exercise allows us to investigate whether, in this theoretical framework, our proposed mechanism can quantitatively account for the large and cyclical changes in the price-to-rent ratio, as well as for the differential evolution in the three regions. Moreover, using the model, we can disentangle the impact of our mechanism from the direct impact of *relative* changes in local discount rates in these locations.

We feed into the model the region-specific parameters β and $\delta = \beta + \gamma$ that capture long- and short-run constraints to housing supply, respectively. We set. $\beta_L = 0.9$, $\beta_{SE} = 0.8$, and $\beta_{NE} = 0.7$ to reflect the fact that the supply price elasticity is lowest in London and highest in the North East, see Table B6. The differences in the $\beta's$ are consistent with the estimated interaction effect for ΔLLD_t with the supply price elasticity in the rent regression in column (6) of Table 1 (-.095). That is, if the difference in the supply price elasticity is one standard deviation (0.61), this translates into a difference of about .095 in the β's, and the supply price elasticity of London is about one standard deviation (two standard deviations) lower than that

[35] We do not use this formulation in the main text as it is not suited well to derive analytically PROPOSITION 3.

of the South East (North East), see Table B6. Moreover, we set $\delta_L = 1$, $\delta_{SE} = 0.95$, and $\delta_{NE} = 0.9$, i.e., assuming very inelastic short-run housing supply.[36]

The parameter ρ captures the degree of persistence in demand, which in the model translates directly into persistence in rent growth expectations. We use Table 4 to derive the degree of perceived rent growth persistence in England. As explained in Section 3.4 in the main text, Table 4 suggests $\rho = 0.95$. There, we also discuss potential reasons for why rent growth expectations may exhibit stronger persistence than changes in our shift-share labor demand measure.

Finally, we feed into the model region- and year-specific discount rates. There is no data available for region-specific discount rates. We therefore approximate regional discount rates based on the evolution of interest rates in England shown in Panel C of Figure 6 and by assuming constant differences in discount rates across markets that reflect differences in idiosyncratic risk and volatility which is typically lower in superstar cities (Amaral *et al.* 2025). We assume that discount rates in London were 0.5 percentage points lower than in the South East and 2.5 percentage points lower than in the North East throughout the sample period. Moreover, we assume that discount rates decreased by 2.5 percentage points in total in each location between 1997 and 2008, the period when the Bank Rate and real mortgage rates fell steadily – the latter from around 5% in 1997 to 2.5% in 2007 and 2008. From 2008 onwards, we assume a stable discount rate because the bank rate did not change much and real mortgage rates moved horizontally, albeit with larger swings. We set initial discount rates to be 5.5% in London, 6.0% in the South East, and 8.0% in the North East. These assumptions imply that the discount rate fell more strongly *in relative terms* in London than in the South East, and more strongly *in relative terms* in the South East than in the North East. The differential relative changes allow for a differential impact of discount rates on the price-to-rent ratios in the three regions that is unrelated to our proposed mechanism. [37]

Figure D1 shows the targeted price-to-rent ratio indices for London, the South East, and the North East. The unexpected demand changes required in the model to generate the observed price-to-rent ratio indices are displayed in Figure D2. These shocks seem plausibly small in magnitude and mostly fall in the range of -0.01. to +0.01 log points.

Figure D3 displays the log difference in the price-to-rent ratio indices shown in Figure D1 as bold black lines. Panel A depicts the difference between London and the North East, and Panel B compares London to the South East. In addition, the figures show as a dashed line the model-generated price-to-rent ratios that would result from the relative changes in discount rates in the three regions *alone*, i.e., when all demand innovations are set to zero. Both panels show that, in the simulation exercise, our proposed mechanism can explain all of the cyclicality in the differences in log price-to-rent ratios and 56.4% (71.5%) of the overall increase in these

[36] Although related to the supply price elasticities shown in Table B6 in a qualitative sense, β is not an inverse supply price elasticity. Rather, it reflects the relationship between the demand shifter and rents. This relationship depends to a great extent on the supply price elasticity.

[37] The secular trend in itself does not affect price-to-rent rations across locations differentially in our theoretical framework. However, relative changes in local discount rates lead to differential changes in price-to-rent ratios and we therefore consider the possibility that the secular trend in real interest rates led to a stronger relative decline in discount rates in locations where housing-related risk was low, such as London.

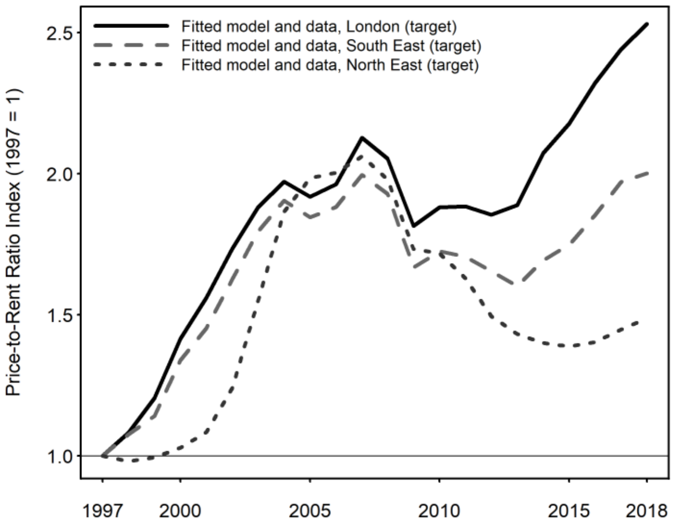
differences between London and the North East (London and the South East) from 1997 to 2018.

Figures D4 and D5 show that the model-generated ratios of prices of rents across locations are comparable to the ratios observed in the data. This is despite the fact that these ratios are not targeted in the calibration.

Finally, Figure D6 investigates whether the model-derived demand innovations for London and the North East coincide with the states of the local economics as observed in the data. We employ regional unemployment rates as a standard measure capturing the local business cycle. Panel A plots the unemployment rates. Panel B shows that unemployment rates were lower in London than in the North East in periods when the demand innovations for London were larger, and vice versa. This strongly suggests that the model-derived demand innovations are highly consistent with the observed state of the local economies of London and the North East – despite the fact that we do not target the unemployment rates in the calibration.

Figure D1

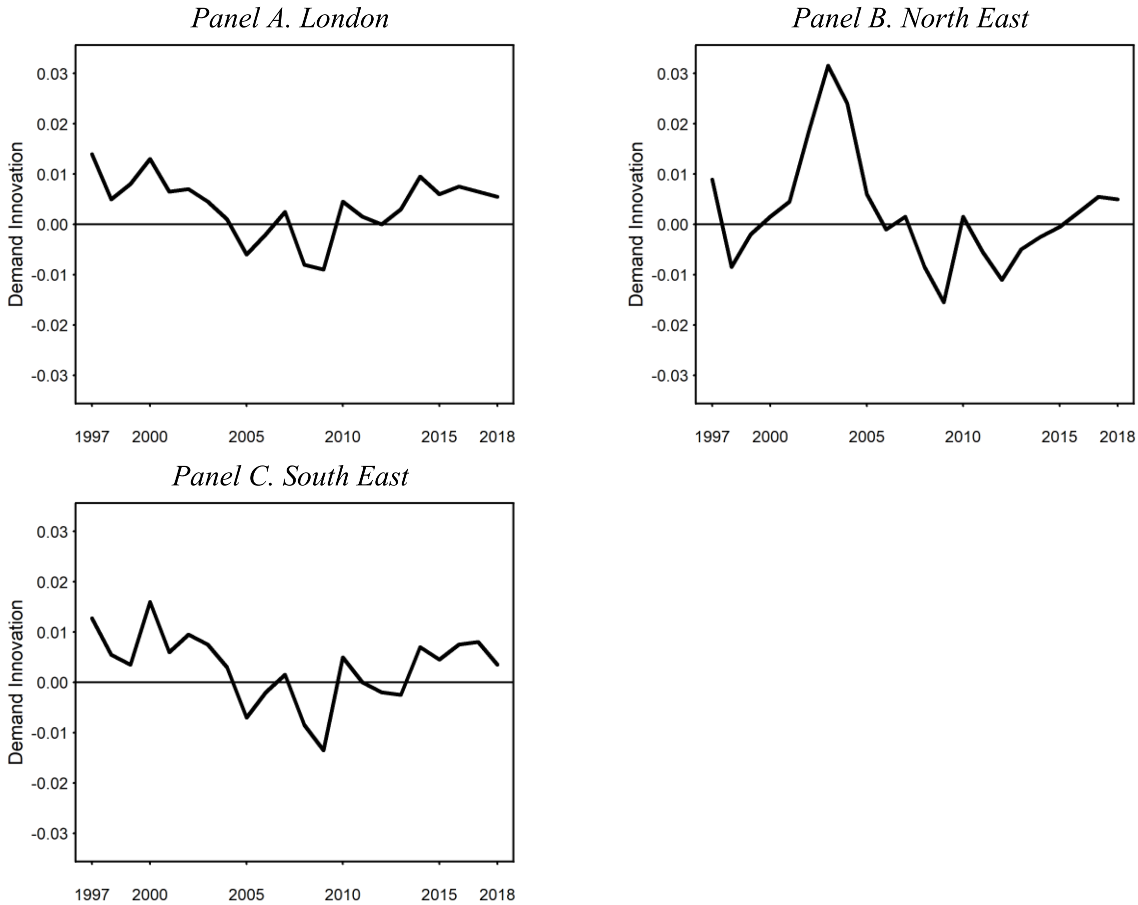
Model-Generated Price-to-Rent Ratio Indices for the Government Office Regions of London, the South East, and the North East



Notes: The figure shows the model-generated price-to-rent ratio indices, which are fit to match exactly the observed data points by choosing a series of region-specific local demand changes illustrated in Figure D2. The assumptions underlying the simulations are described in Section D.1.

Figure D2

Model-Implied Shocks to Housing Demand

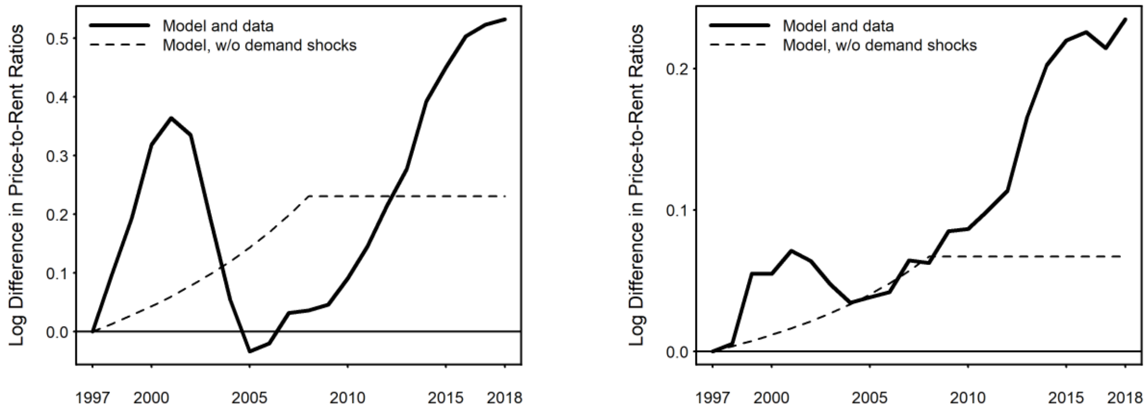


Notes: The figure displays the demand innovations required to fit the model-generated price-to-rent ratio indices to the observed indices, as shown in Figure D1. The assumptions underlying the simulations are described in Section D.1.

Figure D3

Model-Generated Differences in Log Price-to-Rent Ratio and Role of Persistent Shocks to Local Housing Demand in Conjunction with Constraints to Housing Supply

Panel A. London vs. North East *Panel B. London vs. South East*

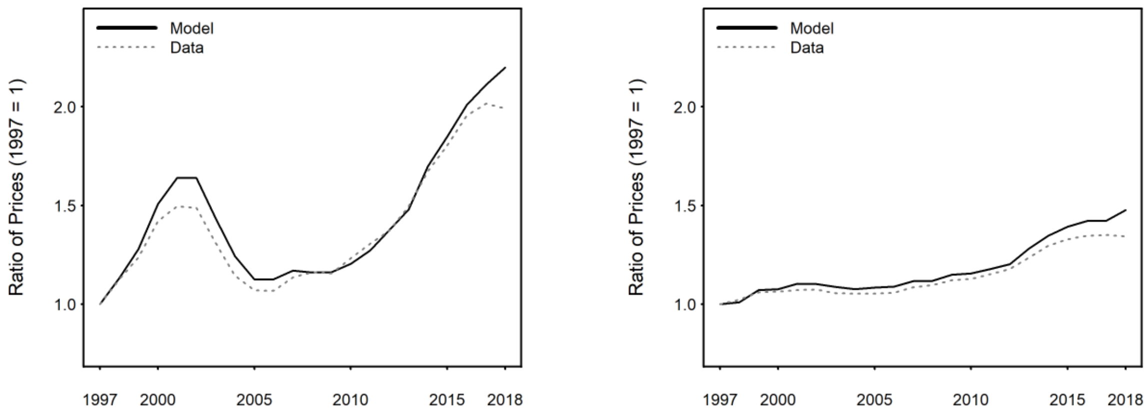


Notes: Panel A compares model-generated price-to-rent ratios in London and the North East. Panel B compares London to the South East. In both panels, the thick black line shows the model-generated differences taking into account demand shocks and location-specific changes in discount rates. The black bold lines match exactly the data. The dashed line depicts the model-generated difference in log price-to-rent ratios under the assumption that demand shocks were equal to zero in all periods. Here, differential changes in relative discount rates across locations explain the evolution of the log difference of price-to-rent ratios. The assumptions underlying the simulations are described in Section D.1.

Figure D4

Model-Implied Ratios of Prices Across Locations

Panel A. London Relative to North East *Panel B. London Relative to South East*

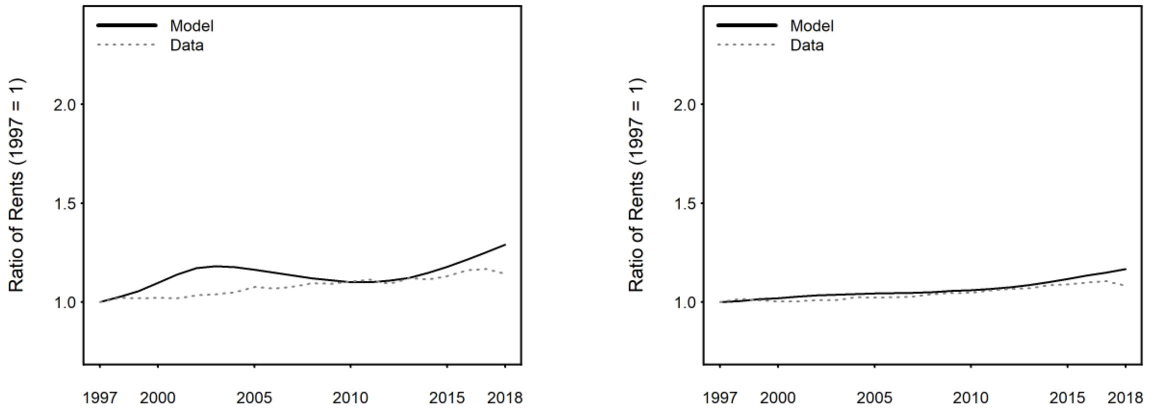


Notes: The figure compares the model-generated ratio of price to the observed difference, indexed to 1997. Panel A (Panel B) displays ratios for London relative to the North East (the South East). The assumptions underlying the simulations are described in Section D.1.

Figure D5

Model-Implied Ratio of Rents Across Locations

Panel A. London Relative to North East *Panel B. London Relative to South East*

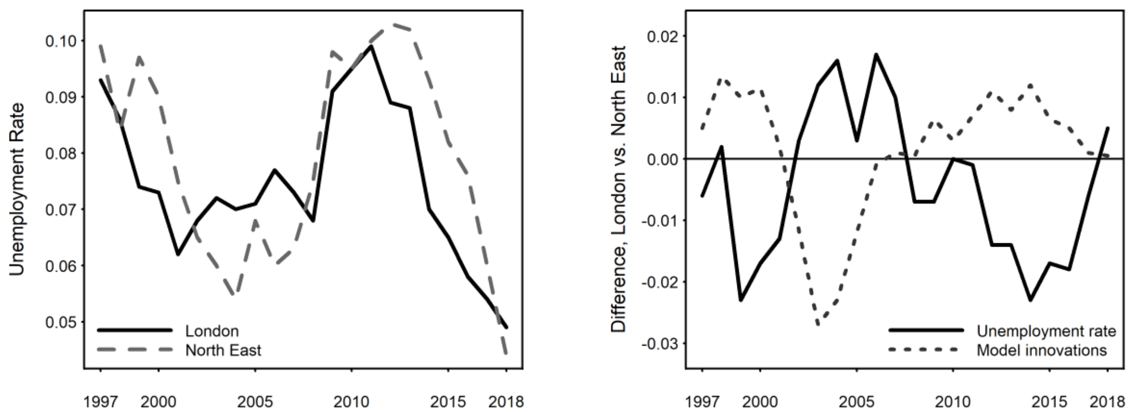


Notes: Notes: The figure compares the model-generated ratio of rents to the observed difference, indexed to 1997. Panel A (Panel B) displays ratios for London relative to the North East (the South East). The assumptions underlying the simulations are described in Section D.1.

Figure D6

Regional Unemployment Rates and Model Innovations in London and the North East

Panel A. Regional Unemployment Rates *Panel B. Differences in Unemployment Rates and Model Innovations*



Notes: Regional unemployment rates in % are provided by ONS. The figure shows the seasonally-adjusted values for Q2 (April – June) in each year, based on the ILO definition. The difference in model innovations is the difference of the lines depicted in Panels B and C of Figure D2.

Finally, the model generates rent expectations for London and the North East that can be compared to the survey evidence. From 2013 to 2015, survey respondents reported average annual expected rent growth to be 1.43 percentage points higher in London than in the North East, which compares to a differential of 1.78 percentage points in the simulation. From 2016 onwards, however, the model-based premium for London rises, while the survey-based premium declines. The same holds true when comparing London to the South East.

D.2 Extension: Brexit-Induced Changes in Regional Demand Expectations and Discount Rates

One plausible explanation for this divergence is the Brexit referendum in 2016, which has differentially affected different parts of England.[38] In particular, Brexit likely had a substantial impact on both short- and long-run demand expectations in England (e.g., Springford 2022, Portes 2023) and contributed to increased uncertainty (e.g., Office for Budget Responsibility 2016, OECD 2016).

Brexit was also widely expected to affect London differently from the more peripheral North East. A report published by the Greater London Authority in 2024 suggests that, unlike the rest of the UK, London's productivity was immediately harmed due to reduced investment and lower migration (Hope 2024). Similarly, Fetzer and Wang (2020) highlight a relatively stronger short-term impact of Brexit on London's economy compared to the North East.

However, consistent with the view that larger and more diverse cities are better able to reinvent themselves and adapt to shocks, the long-term effects were widely expected to be less severe in London than in the North East. Whitehall projections for a 'no deal' scenario, published in January 2018, predicted an 8 percent reduction in gross value added (GVA) for London by 2033, while the North East was projected to experience twice the impact – largely due to its greater exposure to EU trade (Stewart *et al.* 2019).

We integrate Brexit into our model through two adjustments: First, we account for 'Brexit expectations' to reflect plausible shifts in housing demand in both London and the North East. To quantify these effects, we rely on Whitehall projections to estimate the medium-term impact (up to 2033) of Brexit on housing demand in the two regions. The projections suggest a 5 percent reduction in London's GVA under a free-trade agreement with the EU, and an 8 percent reduction in the event of a 'no deal' Brexit. For the North East, the corresponding reductions are 11 percent and 16 percent, respectively.

For 2016, we assume that the anticipated reduction in housing demand by 2033 corresponds to the projected decline in GVA under a free-trade agreement with the EU. Given the challenging nature of EU negotiations, we assume that expectations shifted to the 'no deal' scenario in 2017 and 2018. In each year, we further assume that agents in the model expect Brexit to occur three years in the future. This assumption reflects evidence from the Decision Maker Panel – a survey conducted in 2017 and 2018 among decision makers in Britain – which shows that expectations about the 'leave' date were progressively revised, with respondents anticipating later 'leave' dates over time (Bloom *et al.* 2019).

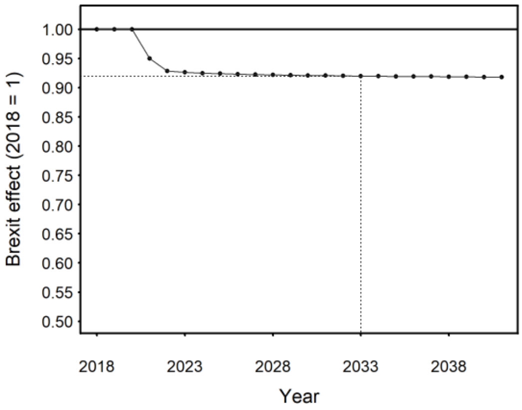
Figure D7 illustrates our assumptions about the expected reduction in demand due to Brexit in London (Panel A), the North East (Panel B), and the South East, as of 2018. These assumptions reflect the view that London's economy experienced an immediate impact, whereas the North East faced a more gradual but ultimately more severe decline.

[38] The referendum essentially coincided with the introduction of a more generous version of the Help to Buy policy in London compared to the rest of the country. In our empirical analysis we control for the differential impact of London's Help to Buy policy by including a dummy variable that equals 1 for London from 2016. This variable may also capture the differential impact of Brexit. We do not model the impact of Help to Buy in our model simulation as we would not expect the policy to have differentially affected long-run demand expectations, in contrast to Brexit.

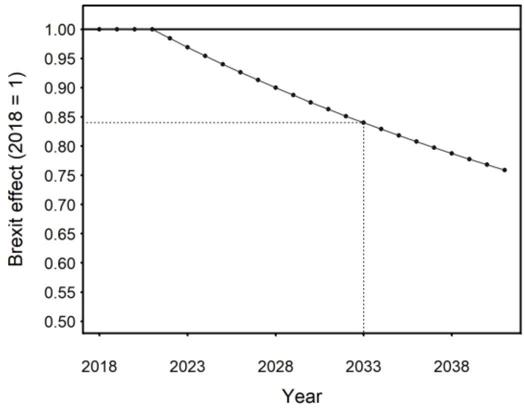
Figure D7

Assumed Impact of Brexit on Demand Expectations in 2018

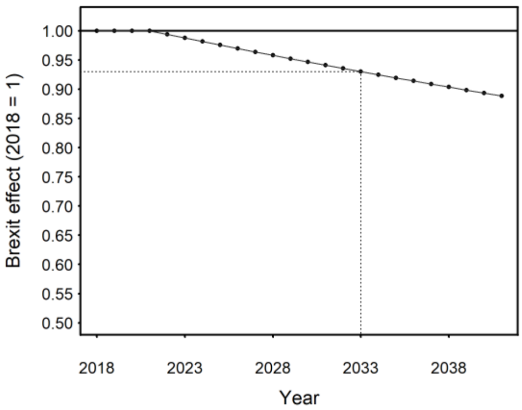
Panel A. London



Panel B. North East



Panel C. South East



Notes: The figure illustrates the assumptions about Brexit's impact on demand expectations for 2018. The thin dotted line indicates the assumption for the year 2033, which is based on Whitehall projections for the impact of Brexit on regional GVA for the 'no deal' scenario. To compute expectations in each year going forward, we employ the following functional form: $index_{rt}^{k} = \phi_r/(\phi_r \ + \ k^{\psi_{rt}})$, where $k > 0$, $t = 2016, 2017, 2018$, and r is the region ($r \ = L, NE, SE$). It captures the relative change in expected demand due to Brexit in region r and as of year t, k years after Brexit. We set the curvature parameters $\phi_L = 0.05$, $\phi_{NE} = \phi_{SE} = 1$, reflecting the different demand schedules implied by the literature, and then determine ψ_{rt} such that the index hits the targeted impact of Brexit in 2033 (as described in Section D.2). In addition, we allow for an immediate impact on demand in London in the year Brexit was expected to happen.

Secondly, Brexit induced substantial political and economic uncertainty, which likely affected discount rates. Evidence from the Decision Maker Panel suggests that firms in the North East were disproportionately exposed to Brexit-related uncertainty, due to the region's relatively high share of exports to the EU (Bloom *et al.* 2019). To account for this, we assume an increase of London's discount rate by 0.25 percentage points, of the North East's discount rate by 0.5 percentage points, and of the South East's discount rate by 0.3 percentage points and in in 2016.

We incorporate these adjustments to expected demand and discount rates into the model simulations. Since we infer the demand innovations required to match the observed price-to-rent ratio indices, this entails recomputing the demand innovations for 2016, 2017, and 2018.

Simulation results for the model extension are summarized in Figures D8 to D12. Figure D8 displays the differences in price-to-rent ratios as targeted by the model, in addition to the hypothetical evolution of these differences as implied by changes in discount rates alone.

The underlying demand innovations used to fit the data are displayed in Figure D9. For 2016, 2017, and 2018, these innovations differ from those reported in Section D.1 (i.e., from the baseline model without Brexit). Notably, the innovations for the North East shown in Panel B of Figure D9 are more positive than those in Panel B of Figure D2. This pattern is consistent with the sharp decline in the North East's unemployment rate during these years, culminating in a record-low level in 2018 (see Panel A of Figure D6).

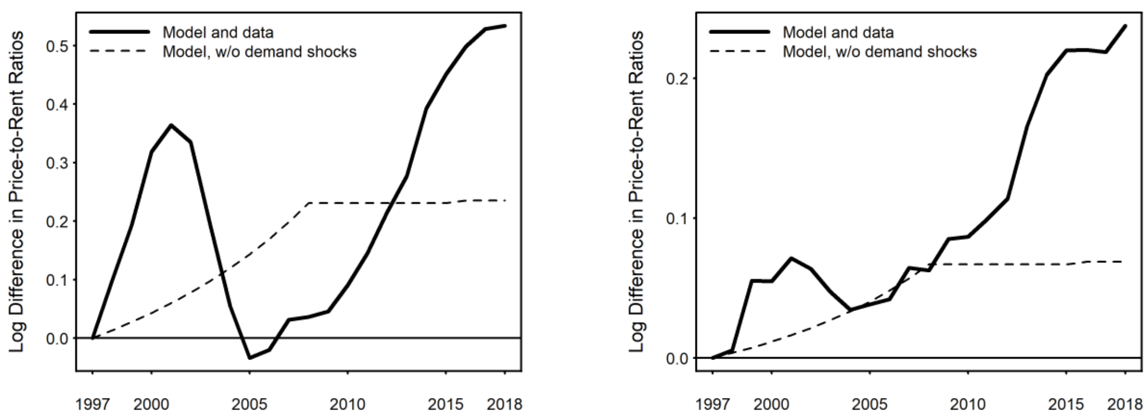
Figure D10 plots the differences in expected average rent growth over the subsequent five years, as derived from the model and as observed in the data. The figures also show the differential expected rent growth generated by the model version without Brexit as a grey long-dashed line. When accounting for Brexit, the model-simulated differential rent growth expectations for the final three years align much more closely with the observed differences in both cases. Notably, in that case, both the model-generated and the survey-based rent expectations decline sharply beginning in 2015.

Figures D11 and D12 plot the ratios of regional house prices and regional rents, respectively, over the sample period. Each panel displays three time-series: the observed regional price and rent ratios (dotted lines), the model version with Brexit (solid black line), and the baseline model described in Online Appendix D (grey long-dashed line). The price and rent ratios in the Brexit and baseline versions of the model are identical until 2015. From 2016 to 2018, the Brexit-adjusted model predictions align more closely with the observed data in both panels. Figure D12 also presents the expected evolution of the regional rent ratio for the period 2019 to 2023 (as of 2018), shown as a fine dashed-dotted line for the Brexit version and a long-dashed line for the baseline model. While the ratio of expected rents increases under the baseline model, it moves horizontally in the Brexit scenario. Taken together, these simulations suggest that Brexit is a highly plausible explanation for the decline in rent growth expectations in London relative to the North East and the South East between 2016 and 2018.

Figure D8

Model-Generated Differences in Log Price-to-Rent Ratio Under the Brexit Scenario

Panel A. London vs. North East *Panel B. London vs. South East*

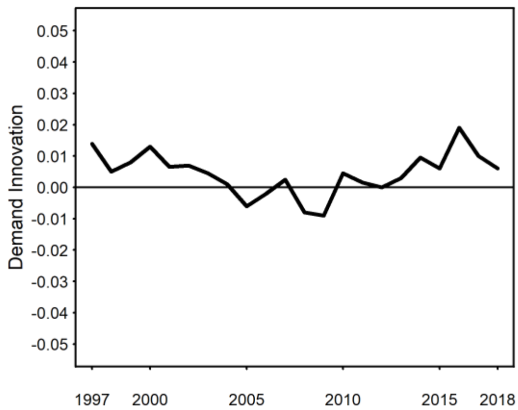


Notes: Panel A compares model-generated price-to-rent ratios in London and the North East. Panel B compares London to the South East. In both panels, the thick black line shows the model-generated differences taking into account demand shocks and location-specific changes in discount rates. The black bold lines match exactly the data. The dashed line depicts the model-generated difference in log price-to-rent ratios under the assumption that demand shocks and expected changes in demand are equal to zero in all periods. The assumptions underlying the simulations are described in Section D.2.

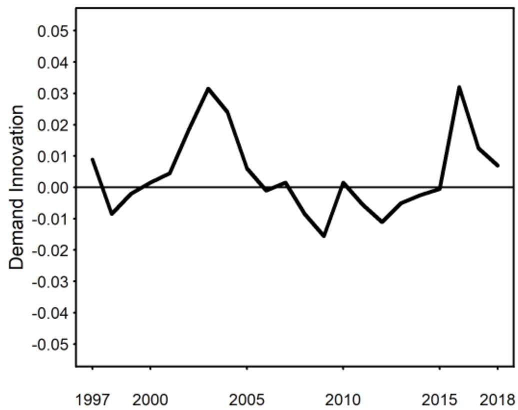
Figure D9

Model-Implied Shocks to Housing Demand in Brexit Scenario

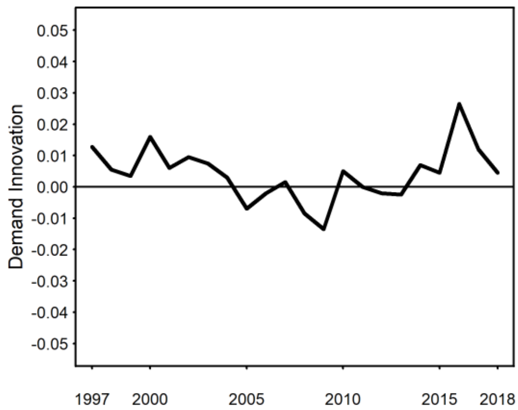
Panel A. London



Panel B. North East



Panel C. South East

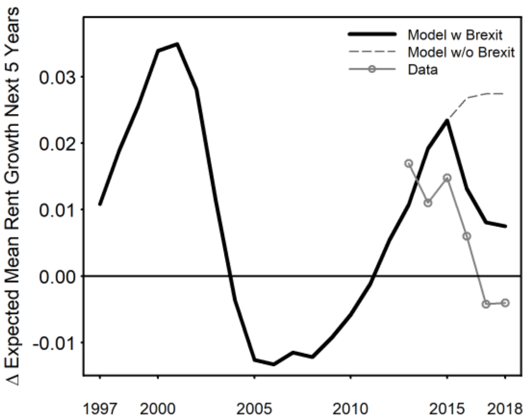


Notes: The figure displays the demand innovations required to fit the model-generated price-to-rent ratio indices to the observed indices. The assumptions underlying the simulations are described in Section D.2.

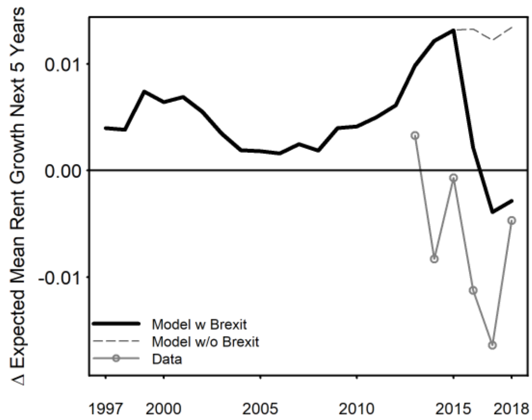
Figure D10

Model-Generated and Survey-Based Differences in Regional Rent Growth Expectations

Panel A. London vs. North East



Panel B. London vs. South East

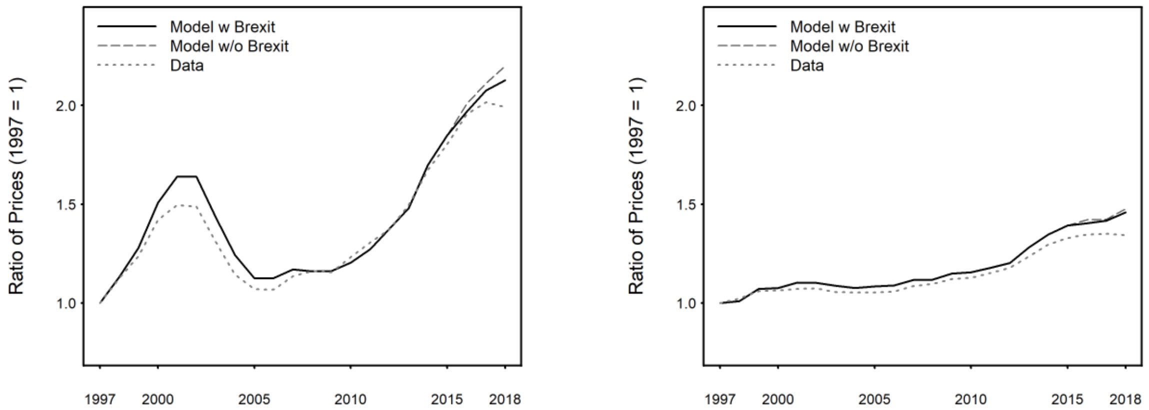


Notes: Panel A compares model-generated and the survey-based rent growth expectations in London and the North East. Panel B compares London to the South East. The assumptions underlying the simulations are described in Section D.2.

Figure D11

Model-Implied Ratios of Prices Across Locations Taking into Account the Brexit Referendum

Panel A. London Relative to North East *Panel B. London Relative to South East*

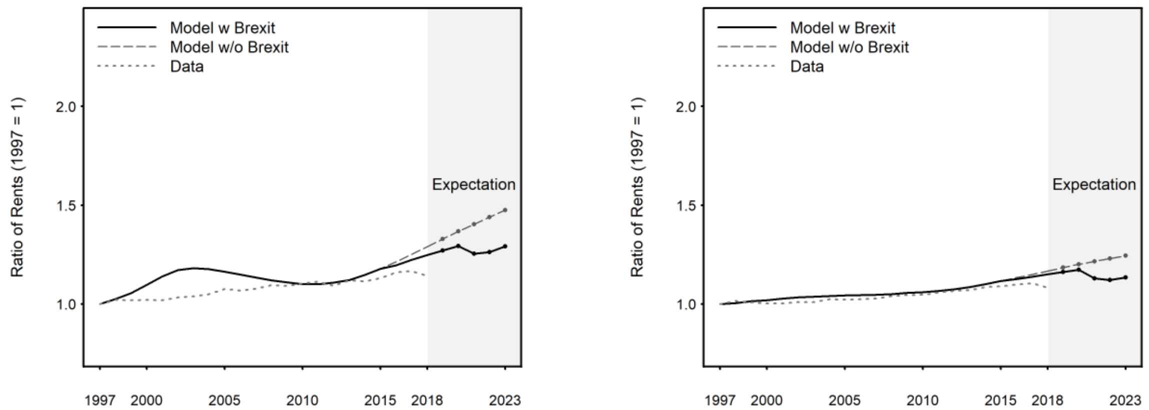


Notes: The figure compares the model-generated ratio of price to the observed difference, indexed to 1997. Panel A (Panel B) displays ratios for London relative to the North East (the South East). The assumptions underlying the simulations are described in Section D.2.

Figure D12

Model-Implied Ratio of Rents Across Locations Taking into Account the Brexit Referendum

Panel A. London Relative to North East *Panel B. London Relative to South East*



Notes: Notes: The figure compares the model-generated ratio of rents to the observed difference, indexed to 1997. Panel A (Panel B) displays ratios for London relative to the North East (the South East). In the grey-shaded area, the figures display the expected ratio of rents going forward, as of 2018. The assumptions underlying the simulations are described in Section D.2.

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