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The determinants of local housing supply in England

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Abstract

We estimate local housing supply elasticities for 325 local authorities and 6,788 census tract areas in England. We examine how housing supply responds to price changes across small areas and how this varies according to a rich set of geographic and policy constraints. Our central estimate for the average elasticity of relative local supply with respect to price across local authorities is 0.14 over a period of 25 years between 1996 and 2021. This is low compared to estimates from other countries. Elasticities are lower in areas with less land available for development, greater differences in elevation, higher historical population density and in areas where local planning authorities had a greater historic tendency to reject new developments. We also find that urban density and constraints on the amount of available land have stronger negative effects on the supply of larger properties than properties with fewer bedrooms.

Keywords: housing supply elasticities, land-use restrictions, productivity
JEL codes: R12, R31, R38, O18, O20

1 Introduction

The response of housing supply to changes in local demand has important implications for changes in average housing costs (Howard and Liebersohn (2021)), affordability and the distribution of wealth (Bourquin, Brewer, and Wernham (2022)). It also impacts where people can live and work, with consequences for the allocation of labour and national productivity (Hsieh and Moretti (2019)) and the geographic sorting of workers by skill (Ganong and Shoag (2017); Gaubert and Diamond (2022)).

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In this paper, we study i) the relative responsiveness of local dwelling stocks in England to changes in housing demand ii) the determinants of housing supply responsiveness and the factors that constrain local housing supply and iii) how the responsiveness of housing supply varies across house types and time periods. To do so we estimate elasticities measuring how relative differences in house price changes translate into relative differences in local housing supply across 325 Local Authorities and 6,788 Middle Super Output Areas (MSOAs) in England over a 25-year period of house price growth and then separately for two 10-year sub-periods.

Our elasticity estimates are based on regressions of local supply changes on local house price growth, allowing for interactions with various supply constraints. Local house price growth is potentially endogenous because it can be driven by shocks to the productivity of local housing supply. We use a control function approach, using a shift-share measure of changes in local labour demand as our instrument, to strip out the effects of endogenous supply shocks when measuring the effect of price changes on quantities. Using this approach, we can also allow the impact of local price changes to vary according to a rich set of local possible constraints, and study their relative importance. This means we can examine local variation in housing supply elasticities, and their determinants in a great deal of detail. We draw on newly released data on the number of residential units at the MSOA level, and combine this with data on an extensive set of constraints, including satellite data on land-use, topographic data on elevation, information on local geological hazards, historic local planning refusal rates (taken from Hilber and Vermeulen (2016)), and digitized maps of land covered by Green Belt, national parks and sites of special scientific interest.

We start by estimating the effect of price changes on supply across local authorities, providing us with a measure of the elasticity of the local housing stock in different areas in response to relative differences in house price growth. Our regression estimates imply a 25-year elasticity of the local housing stocks to price changes of 0.14 over the boom period from 1996 up to 2021.[1] Over the 10-year period from 1996-2006, when house prices rose most steeply this elasticity was 0.1. The elasticity over the following period from 2011-2021 is even smaller. These estimates imply that the response of local housing supply to differential price changes in England is small. Using comparable methods, Baum-Snow and Han (2024) estimate 10-year house price elasticities across across US census tracts over the period

[1]Our estimates are based on differences in housing supply across areas, and so they measure how many extra homes are built in areas with higher house price growth relative to others. These do not necessarily correspond to the elasticity of the national housing stock with respect to national house price growth (as they net out any common increases or increases in housing supply that affect all areas). However, it is noteworthy that our estimates are quite close to estimates of the national stock elasticity taken from time series models. OECD (2011) estimate a flow elasticity for the UK of 0.40 over a 20-year period and Swank, Kakes, and Tieman (2003) estimate a flow elasticity of 0.45. Miles and Monro (2020) show that a flow elasticity of 0.4 is consistent with an elasticity of the dwelling stock of 0.08.

2001-2011, and obtain an elasticity for the number of housing units of 0.3. This is larger than our estimates despite the fact they use smaller units of geography, which typically leads to imply lower elasticities (for example, they estimate regional level elasticities of 0.41).

We then study heterogeneity in the responsiveness of local supply to different geography and policy constraints at level of MSOAs (census tracts). We find that supply elasticities are lower in areas with greater pre-existing urban development, less land available for construction, greater topographic constraints and geo-hazards and in local planning areas with a greater historic tendency to refuse new developments. Our empirical approach has the advantage of allowing us to decompose the relative importance of these different (potentially correlated) constraints. We find that the share of land available for development and pre-exisiting urban density are the most important determinants of variation in local housing supply responses, together accounting for 80% of the variation across areas. Uneven elevation accounts for an additional 14%.

The housing stock data for the period 2011-21 contains richer information on the type of properties in each MSOA which allows us to examine how different constraints affect the number of housing units for homes of different sizes. The share of land available for development has a greater negative impact on the supply of larger homes. This implies that land-use restrictions - such as Green Belt designations - affect the types of homes that are built as well as the number, with potential implications for the local demographic mix (for example, if a shortage of family homes affects fertility, Kulu and Vikat (2007)). Pre-existing density and refusal rates also mean that new properties are smaller, with areas that are more constrained in these dimensions increasing the local proportion of properties with fewer bedrooms by more when prices increase.

We can use our results to perform a back-of-the-envelope calculation to study how changes in local constraints would have affected price growth for a given set of labour demand shocks. Our estimates imply that had elasticities in London - an inelastic area - been equal to the median elasticity in England, prices there would have risen 21 percentage points less than they did in practice.

Finally, we examine which local authorities are associated with larger positive residuals from our estimated supply equation. These areas saw greater quantity growth than we would expect given their local house price changes and constraints. Prominent among these areas are boroughs in East London, including the City of London and Tower Hamlets. Tower Hamlets and surrounding areas were part of a large scale urban regeneration scheme following the London Olympics, involving the creation of an independent planning authority to coordinate development and significant investment in local infrastructure.

Our paper contributes to a literature studying local variation in housing supply elasticities. In an early and important contribution to this body of work, Saiz (2010) examines the role of geographic and policy constraints in determining housing supply in US cities over the a 30-year period from 1970 to 2000. He obtains a weighted average long-run elasticity across metro areas of 1.75 and finds that supply elasticities are much lower in land constrained cities such as Miami, New York, Los Angeles and San Francisco. More recently, Baum-Snow and Han (2024) estimate supply elasticities at census tract level in the US. They also estimate elasticities along different margins, including floor space, number of units and land covered by development, obtaining elasticity estimates of 0.4, 0.3 and 0.1 respectively for the period 2001-2011. Chapelle, Eyméoud, and Wolf (2023) estimate an overall supply elasticity of 0.5 for French cities over the period 2000-2010, finding that these vary according to local refusal rates and the share of land available for development. Beze (2023) estimates a floorspace elasticity of 0.22 and a housing unit elasticity of 0.25 using variation across 401 German districts for the period 1998-2019. He finds limited heterogeneity by the amount of land available but that prior development is a significant source of variation. Büchler, v. Ehrlich, and Schöni (2021) document significant geographic heterogeneity in local supply elasticities for Switzerland. Their estimates imply a price elasticity of 0.42 over the period 2005-2015.

The main contribution we make relative to these earlier papers is the use of a control function approach which allows us to simultaneously examine the roles of many different (possibly correlated) supply constraints and assess their relative importance. This means we are able to present a very rich picture of the variation in housing supply elasticities across areas. A further contribution we make is providing new evidence on how different constraints affect the supply elasticities for properties of different sizes, showing that constraints on land-use and pre-existing developments mean that marginal properties are smaller.

Differences in the time periods, scale of the geographic areas and methodologies used in different settings all complicate making direct comparisons of estimates across countries. Nonetheless, taking the most comparable estimates from these other studies suggest that housing supply elasticities in England are particularly low. This likely reflects the stringency of English regulations, particularly in and around major urban areas which are protected by the Green Belt. The Green Belt surrounding London, for instance, is the largest in the country. By comparison, Chapelle et al. (2023) find that the French capital, Paris, is not much more inelastic than other cities as housing supply is relatively flexible in its outlying suburbs.

A related UK-based study is Hilber and Vermeulen (2016) who compare the relative roles of land availability and planning policy in determining the responsiveness of house prices to local earnings growth across 353 English local planning areas. Their estimates imply that house prices in the South East of England would have been roughly 25% lower in 2008 if the region had planning regulations of similar restrictiveness as the North East of England. Our paper differs from this study in that we directly estimate the elasticities of the housing stock with respect to price changes (rather than the price-earnings elasticity) and that we use data on local constraints at a much finer geographic level.

The rest of this paper is structured as follows. Section 2 describes the UK policy context and more recent changes aimed at boosting housing supply. Section 3 describes the data we use and discussed long-run trends in price and quantity growth. Section 4 describes our empirical approach and present our estimates of housing supply elasticities, how they vary with constraints and how they affect the local housing mix. Section 5 concludes.

2 Housing policy in the UK

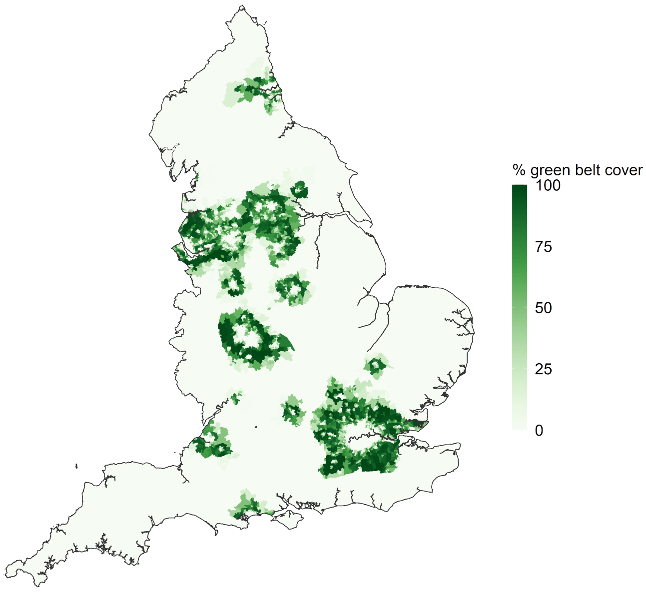
Restrictions on home building in the UK are tight, and are often blamed for making housing in the UK more expensive, cramped and lower quality than in other developed countries (Hilber & Schöni, 2016).

Decisions around house building in England fall under the responsibility of 393 Local Planning Authorities (LPAs).[2] These LPAs often align with Local Authority Districts, but also include, for instance, national park authorities. Decisions are made by local elected representatives, whose existing voters will typically see many more of costs from greater development (such as congestion and reduced access to green spaces) than the benefits, giving them an incentive to be conservative. Decisions are also typically made on a largely case-by-case basis, rather than LPAs pre-specifying criteria required for approval (as in other countries where 'zoning' of areas for certain development types is more common), adding unpredictability to the planning process. In addition, because the costs of administering planning policy are often large, there are often delays in processing applications (Meen & Whitehead, 2020).

Specific regulations also apply to broad areas of English countryside, including national parks, areas of outstanding national beauty, sites of special scientific interest and to designated land surrounding major cities known as 'Green Belt'. The Green Belt is aimed at containing urban sprawl and preventing neighbouring urban areas from merging. New building in these areas is considered inappropriate unless for uses that "preserve the openness of the Green Belt", such agriculture, indoor or outdoor recreation, cemeteries, and allotments (Ministry of Housing, Communities and Local Government (2021)). There are exceptions for the redevelopment of previously developed land and limited affordable housing devel-

[2]Planning rules differ across the nations of the UK. Our analysis focuses on England.

Figure 1: Share of land covered by Green Belt



Note: Figure shows the share of land covered by green belt across MSOAs in England. Data taken form Ministry of Housing, Communities and Local Government.

opment. Figure 1 shows the share of each MSOA covered by Green Belt. The largest area of Green Belt is around London, which accounts for around one third of the total Green Belt in the country (Meen & Whitehead, 2020). Koster (2024) finds, using a quantitative spatial model, that the Green Belt reduces housing supply and raises prices in major English cities by 5-20% (but also that it associated with positive overall welfare effects because it generates local amenities).

In more recent years, the national government took several steps to encourage more house building. Rights were granted in 2012 to convert offices and other non-residential spaces into housing without the need for individual planning permission (adding about 100,000 homes to the English housing stock between 2015/16-2022/23, Rankl (2024)). Since 2018, progress towards local house building targets has been assessed through housing delivery tests. The penalties for failing to meet the goals originally took the form of reducing local authorities' discretion to refuse new developments, but the targets have since been made advisory only.

Another policy is the 'help-to-buy' scheme which provided subsidised credit to purchase new-build properties in England. The focus on new-build properties was meant to encourage new supply. Carozzi, Hilber, and Yu (2024) exploit local discontinuities in eligibility for the scheme to measure its impact on local housing supply. They find no impact of more generous subsidies in Greater London but some effect on relative construction volumes along the Welsh-English border. They conclude that supply constraints in London reduced the impact of the scheme on supply relative to its neighbouring areas, while supply along the Welsh border was more elastic leading to greater effects.

In what follows we report housing supply responses separately for the period 2011 - 2021, which includes the effects of these more recent policy changes.

3 Data

Local house prices and quantities

We use data on the number of housing units taken from the Valuation Office Agency at the level of 6,788 Middle-Super Output Layers (MSOAs) in England. MSOAs can also be aggregated into 325 local authorities (LAs). By observing the number of dwellings, we can measure changes in housing stocks. This differs from 'flow' measures of housing supply in that it reflects demolitions and conversions. From around 2004 onwards, we can also observe reliable local counts of the number of properties by size (measured by the number of bedrooms) and type (e.g. flat, detached house etc.).[3]

Our measures of local house prices are calculated using the universe of housing transactions from the UK Land Registry, which is available from 1995. We construct a hedonic-adjusted measure of local house prices to correct for quality differences among homes sold in any given year. Specifically, we regress log house prices on dummies for property type, calender month of purchase, whether the property is new-build and tenure type (whether the property is leasehold or freehold) and interactions between either MSOAs or LA fixed effects and year dummies. Local prices in each year are values of the interacted fixed effects. We also deflate house prices using the Consumer Price Index to put them in real terms.

In what follows, we study housing supply changes over the 25-year period from 1996 (the trough of house prices in the 1990s) to 2021. We also make use of two ten-year subperiods of real house price growth. The first is a boom period lasting from 1996-2006 (corresponding roughly to the trough to peak of house prices ahead of the financial crisis).[4] The second period lasts from 2011-2021 (roughly from the post-crisis trough in house prices until the most recent year of our data).

3.1 Trends in house prices and housing supply

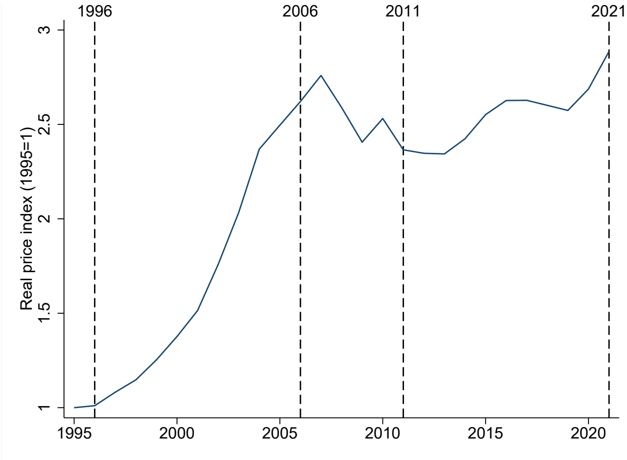
Figure 2 shows real house prices between 1995 and 2022 nationally, calculated using our quality adjusted house price measure. Taking the whole of our analysis period, 1996-2021, together, almost tripled in real terms - increasing by a total of 189%.

[3]Prior to this year, a large share of properties are classed as having unknown size and property type. This falls to less than 2% by 2004 and to less than 1% by 2011.

[4]The actual peak was in 2007.

The increase in house prices was fastest in the years leading up to the great recession. In our first sub-period - between 1996 and 2006 - real prices rose by around 160%. In the wake of the financial crisis, real house prices declined, reaching a trough in 2013 before recovering - slowly at first. A further increase in national house prices occurred in 2020 and 2021, buoyed by a temporary cut in stamp duty (a property transactions tax) and the accumulation of household savings during the periods of lockdown in 2020 and 2021. In our second sub-period, from 2011 to 2021, prices rose by a total 22%.

Figure 2: Real house price levels in England, 1995-2021

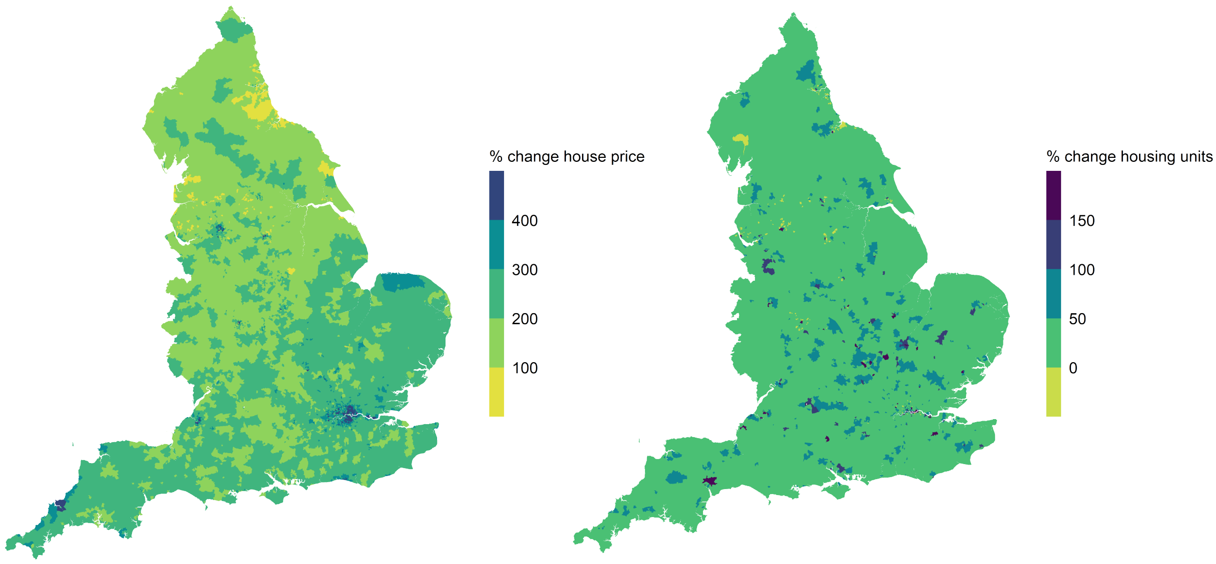


Note: House prices are taken based on transactions data taken from UK land-registry. Prices are quality adjusted to account for house type and tenure (leasehold or freehold) and deflated with the Consumer Price Index.

These national changes mask considerable differences across areas. Panel (a) of Figure 3 shows the pattern of house price increases during the period 1996-2021 across MSOAs in England. There is significant variation, with house price growth tending to be higher in cities such as London, Manchester and Bristol. In some areas of these cities, prices rose by over 400%. Panel (b) shows by contrast that quantity growth was much more uniform across MSOAs, with isolated areas of larger housing growth largely disconnected from the areas of most rapid price growth. In Brighton and Hove on the South coast of England, for example, house prices grew by 370% whilst supply grew by just 12%.

Figure 3: Local house price and quantity growth across MSOAS, 1996-2021

(a) Real house price growth % (b) Growth in dwelling stock %



Note: House prices are taken based on transactions data taken from UK land-registry. Prices are quality adjusted to account for house type and tenure (leasehold or freehold) and deflated with the Consumer Price Index. Dwelling stock data is taken from the Valuation Office Agency.

Simple comparisons of price changes and quantity growth in different areas suffer from simultaneity bias. In the following sections, we recover causally how relative differences in local demand for housing translate into differences in local supply.

4 Local housing supply elasticities

To recover local housing supply elasticities, our empirical approach will be to estimate the following supply equation

$$\Delta \log Q_i = \gamma \Delta \log P_i + \beta X_i + u_i \tag{1}$$

where Q_i is the quantity of housing stock, P_i house price in location i, and X_i is a vector of local area controls. The coefficient of interest γ represents the average elasticity of housing supply across areas with respect to price, that is, the percentage change in housing stock given a 1% change in property prices.

OLS estimates of this equation may be biased if price changes are driven by supply side shocks (such as changes in the productivity of the local construction industry, or changes in local regulations). There may also be measurement error if estimates of local house prices are based on a small number of transactions. This would introduce correlation between $\Delta \log P_i$ and the error term u_i, hence we require an instrument for house price growth that is unrelated to local supply conditions.

The classic approach to recovering supply elasticities is to use an instrument that shifts housing demand. One such factor is the demand by employers for local workers. This is likely to vary over time and across areas according to the comparative advantage of areas in different industries, whose employment rates rise and fall according to global demand for their output and changes in technology. Our aim is to isolate changes in local labour demand due to such global factors, as opposed to potentially endogenous local drivers of employment (such as shocks to local housing supply).

To implement this, we use an instrument for local labour demand: the shift-share predicted measure of the change in 'residential market potential' (RMP) proposed in Baum-Snow, Hartley, and Lee (2019).[5] This is defined in Equation 2 for local authority i in year t.[6]

$$\Delta \log \widetilde{RMP}_{i,t} = \log\left(\sum_j \tilde{L}_{j,t} e^{-\omega \tau_{ij}}\right) - \log\left(\sum_j \tilde{L}_{j,t-1} e^{-\omega \tau_{ij}}\right) \tag{2}$$

where ω is the coefficient on time costs in a gravity regression of commute flows between different areas, τ_{ij} is the average commute time between areas i and j (assumed to be constant across years), and where

$$\tilde{L}_{i,t} = \frac{\left(E_{ik,t_0} \times \frac{E^{-i}_{k,t}}{E^{-i}_{k,t_0+l}}\right)}{E_t} \tag{3}$$

Here E_{ik,t_0} is the employment in industry k in location i and some base year t_0, $E^{-i}_{k,t}$ is total employment in industry k in all locations apart from i in year $t > t_0 + l$, and E_t is total employment in all locations and industries in year t.

This instrument combines two features. The first is the shift-share instrument for jobs in area i ($\tilde{L}_{i,t}$), which reflects local labour demand (Bartik, 1991). This is a measure of the predicted number of local jobs given employment shares of different industries in an area from some initial period, and *national* employment growth in each industry (excluding employment for the area in question). The idea is that this captures employment levels in different areas that is due to national growth trends in different industries, as opposed to local factors (housing supply shifters that affect both local employment growth and house prices). In our analysis we take initial industry shares from 1991 which preceded the precipitous rise in house prices from the mid-1990s onwards.

[5]A closely related concept is 'residential market access' (RMA) which is derived from a spatial equilibrium model of workers' location choices (Baum-Snow & Han, 2024). We describe this measure and how we calculate it in our setting in Appendix A2.1. In practice, we find that this is highly correlated with the simpler RMP measure. We discuss results with this alternative instrument, calculated separately within different regions, in Appendix A3.

[6]Detail on the data used to construct the instrument can be found in Appendix A2.1.

The second feature of this instrument - useful for an application where we study small geographic areas - is that jobs growth in a given area is a weighted sum of jobs growth in all localities (according to their accessiblity). The weights, ω, reflect the time costs of reaching different possible commute destinations. This feature accounts for the fact that an area might become a more desirable location to live in because there is growth in the employment opportunities in common commute destinations as well as the area itself (see Manning and Petrongolo (2017)). We use this instrument because, in smaller geographic areas such as LAs, a large fraction of residents commute to work outside the area. For instance, many Travel to Work Areas (TTWAs) in England whose boundaries approximate self-contained areas in which residents live and work comprise multiple local authorities.

We estimate ω, the time-cost of commuting, via a gravity model incorporating log commute flows across all local authorities, and average commute travel times, using the National Travey Survey. Further details of our approach can be found in Appendix A2.1. We also test robustness to estimating a separate gravity model (and therefore ω and τ_{ij}) for 10 metro-regions we have constructed, to reflect possible differences in travel costs. Results using these alternative instruments, which we use alongside regional fixed effects, are very similar to our main results (see Appendix A3).

Our main specifications control for lagged area population characteristics capturing education (share with a degree) and age composition (share who are aged 60 and over) from 1991. These account for potential supply side changes (e.g. changes in regulation) in response to the preferences of local residents. We also control for house prices in the year prior to each period we consider to account for mean reversion in prices. As we show below, our results are not affected much when we adjust this control set.

Relevance of the instrument

The first stage regression we run is

$$\Delta \log P_i = \pi \Delta \log \widetilde{RMP}_i + \theta X_i + v_i \tag{4}$$

We report the first stage estimates in Appendix A3. The instrument is strongly significant in all three time periods we consider. The first stage using the RMP instrument yields an F statistic of 17 for the period 1996-2021.

We also compare first stage performance of the predicted RMP measure, log change in $\widetilde{RMP}$, with a standard Bartik instrument based solely on each area's own predicted change in employment (i.e. the log change in $\tilde{L}_{i,t}$) in Table A4. The two approaches perform similarly for the time periods 1996-2021 and 1996-2006, but the standard Bartik has a poor first stage performance in the sub-period 2011-2021. We believe this is because the standard Bartik instrument is not as an accurate a measure of local labour demand changes for the small geographies we use in our analysis.

Rather than presenting results using two stage least squares (2SLS), we take estimates of the first stage residuals, $\hat{v}_i$, and include these as an additional 'control function' in our supply equation (bootstrapping standard errors to account for use of generated regressors). With a single endogenous variable, this yields identical estimates to 2SLS. However, the control function approach also allows to account for potentially endogenous price changes in a model where we include many interactions between prices and various supply constraints. As we describe below, in this case, it will potentially differ from 2SLS, and makes different assumptions.

4.1 Housing supply elasticity estimates

Table 1 shows estimates of housing supply elasticities for local authorities across the whole period 1996 - 2021, early period 1996 - 2006 and later period 2011 - 2021. We report results using the OLS estimator, with and without controls, a specification including the control function and a specification which additionally controls for region fixed effects. The results using the control function are similar to those from OLS, which is consistent with the idea that most of the variation in price growth across areas is driven by demand-side factors. Our preferred specification is column (3).

Our estimates imply that, over the whole period 1996-2021, local authorities that saw a greater 10% increase in local house prices saw a 1.4% greater increase in the local dwelling stock. This estimate is not greatly affected when we add controls or the control function to account for possible endogeneity in prices. Elasticities are smaller in the 10-year subperiods 1996-2006 and 2011-2011. There is not much evidence for any change in the responsiveness of supply to demand changes between these two periods, despite the policy changes described in Section 2. The difference in the short and long-run elasticities is consistent with a lagged response of construction activity to price increases.

Table 1: National LA housing supply elasticity: dependent var Δ log Q

	OLS	plus controls	plus control func.
Panel A: 1996 - 2021			
Δ log P	0.120***	0.142***	0.142
	[0.079,0.162]	[0.094,0.191]	[-0.012,0.287]
$\hat{v}_i$			0.000
			[-0.261,0.020]
R2	0.139	0.178	0.178
Observations	325	325	325
F-stat			17.13
Panel B: 1996 - 2006			
Δ log P	0.077**	0.077**	0.101
	[0.028,0.127]	[0.026,0.128]	[-0.071,0.264]
$\hat{v}_i$			-0.027
			[-0.278,0.041]
R2	0.039	0.042	0.043
Observations	325	325	325
F-stat			10.62
Panel C: 2011 - 2021			
Δ log P	0.101***	0.070***	-0.034
	[0.065,0.138]	[0.037,0.104]	[-0.285,0.223]
$\hat{v}_i$			0.107
			[-0.108,0.377]
R2	0.112	0.190	0.192
Observations	325	325	325
F-stat			7.71

Notes: $\Delta LogP$ is the change in quality adjusted house prices. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in the year prior to each period of house price growth. The regressions are also weighted by number of housing units in each LA in that year.

Table 2 shows results from regressions at the level of MSOAs rather than LAs. The results from the OLS specifications in columns (1) and (2), may differ from those in Table 1 if quantities are more or less responsive to price signals within LAs than they are across LAs. The OLS across MSOAs results imply smaller elasticities than comparisons across LAs, suggesting that even within LAs houses are not much more likely to be built in locations with faster price growth. Results in column (3) use a control function based on our instrument which is constructed at LA level, and so does not exploit variation in demand changes across MSOAs. These results differ from those in the same column (3) in Table 1 because the controls for lagged prices now are at the MSOA level rather than LA level. We include this column for completeness. It also implies lower elasticities than we estimated at LA level.

Table 2: National MSOA housing supply elasticity: dependent var Δ log Q

	OLS	plus controls	plus control func.
	Panel A: 1996 - 2021		
Δ log P	0.098***	0.087***	-0.009
	[0.068,0.129]	[0.055,0.119]	[-0.103,0.084]
$\hat{v}_i$			0.114**
			[0.035,0.203]
R2	0.025	0.027	0.031
Observations	6,788	6,788	6,788
F-stat			54.67
	Panel B: 1996 - 2006		
Δ log P	0.048**	0.056***	-0.084
	[0.013,0.084]	[0.024,0.087]	[-0.213,0.047]
$\hat{v}_i$			0.153***
			[0.124,0.331]
R2	0.005	0.019	0.023
Observations	6,788	6,788	6,788
F-stat			23.34
	Panel C: 2011 - 2021		
Δ log P	0.069***	0.048***	-0.037
	[0.045,0.093]	[0.026,0.070]	[-0.125,0.051]
$\hat{v}_i$			0.091**
			[0.044,0.213]
R2	0.013	0.027	0.028
Observations	6,788	6,788	6,788
F-stat			65.99

Notes: Standard errors are clustered at LA level. $\Delta LogP$ is the change in quality adjust house prices. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in the year prior to each period of house price growth. The regressions are also weighted by number of housing units in each MSOA in that year.

4.2 Validity of the shift-share instrument

The shift-share instrument we use is what Borusyak, Hull, and Jaravel (2024) refer to as a formula instrument, in that it combines pre-determined local employment in different industries with shocks to nation-wide employment through the formula defined in equation

(2). In recent years, there have been several advances in our understanding of the assumptions required by such formula instruments, and shift-share instruments in particular, to ensure their exogeneity.

In cases when the formulae used are linear functions of many shocks, Borusyak, Hull, and Jaravel (2022) show that conditional mean-independence between the shocks and the error term is sufficient to ensure orthogonality of the instrument. However, the formula we use is clearly highly nonlinear, and in this case, exogeneity of the shocks is not itself sufficient (Borusyak & Hull, 2023), as it can introduce an omitted variable bias that depends on the variance-covariance matrix of the shocks and its interaction with local industry shares. One solution to this problem, suggested in Borusyak et al. (2024), is to linearise the instrument. We do this by taking a first order approximation to log $\widetilde{RMP}$, making it a linear function of shocks. We do this in Appendix A4. This linearised IV yields very similar estimates to our main specification, giving us confidence that the use of a nonlinear instrument is not biasing our results.[7]

Goldsmith-Pinkham et al. (2020) also discuss how estimates from Bartik shift-share instruments can in practice be highly dependent on particular industry shares, and suggest a decomposition of estimated coefficients into 'Rotemberg-weights' to check this and whether the exogeneity requirements of the instrument are plausible. This is not possible in our nonlinear instrument, but we show that our linearised instrument can be decomposed into a linear function of shifts and shares. This allows us to decompose our estimated effects into the contributions of different industries and destinations. Appendix A4 sets out the results for the regression of changes in the log housing stock and changes in log prices over the period 1996-2021. The five industries that make the largest positive contributions are in order: "Activities auxiliary to financial services and insurance activities", "Crop and animal production, hunting and related service activities", "Manufacture of fabricated metal products, except machinery and equipment","Food and beverage service activities", and "Computer programming, consultancy and related activities". These industries account for 38% of the positive weight of the estimator, which is lower than in any of the example cases discussed in Goldsmith-Pinkham et al. (2020). Reassuringly, these sectors are not themselves likely to be associated with the supply of housing. In addition, we show in the Appendix that industries with these shares are not correlated with the most obvious supply shock - changes in

[7] Goldsmith-Pinkham, Sorkin, and Swift (2020) discuss an alternative assumption that can justify the validity of both linear and nonlinear shift share instruments. The assumption they make is that, conditional on the industry shocks, the error term is mean independent of the local employment shares after partialling out the effect of controls. This is analogous to the parallel trends assumption in difference-in-difference studies, and in our case would imply that, were it not for the differences in employment growth in different industries, trends in housing supply would not have differed systematically across areas (or, in other words, there are no unobserved supply shocks that are correlated with local industry shares). This assumption is in many ways stronger than the assumption imposed by Borusyak et al. (2022), but we believe it is also plausible in our context.

local planning refusal rates.

4.3 Heterogeneity in supply elasticities

We now turn to studying heterogeneity in supply elasticities according to local supply constraints. To characterise this heterogeneity, we allow elasticities to vary across areas according to their different geography, geological and policy constraints.

That is, we estimate

$$\Delta \log Q = \gamma \left(Z_i\right) \Delta \log P_i + \beta X_i + \Delta u_i \tag{5}$$

where Z_i is a vector of local supply constraints. We choose a linear function for $\gamma\left(Z_i\right)$

$$\gamma\left(Z_i\right) = \gamma_0 + \sum_{\ell} \gamma_\ell Z_{i,\ell} \tag{6}$$

where $Z_{i,\ell}$ is the ℓth component of the vector Z_i. In principle, this equation could be estimated using two-stage least squares (2SLS), instrumenting interactions of $Z_{i,\ell} \times \Delta \log P_i$ with $Z_{i,\ell} \times \Delta \log \widetilde{RMP}_i$. In practice, when Z_i has many elements, identification of $\gamma\left(Z_i\right)$ via 2SLS would be extremely challenging, requiring many instruments that independently drive variation in each interaction term.

Rather than attempt to proceed with 2SLS, we therefore employ a control function approach, including a control for the endogenous element of prices in our supply equation.

$$\Delta \log Q_i = \gamma(Z_i) \Delta \log P_i + \beta X_i + \zeta \hat{v}_i + \omega_i \tag{7}$$

As above, the first stage residuals account for the endogenous component of house price increases, However, in this model, it only does so by making stricter assumptions than 2SLS (Imbens and Wooldridge (2009)).[8] We test the sensitivity of results to relaxing some of these assumptions below.

The vector of supply constraints we use contains:

- **Flood risk.** This is measured as the median risk of flooding from rivers or the sea across postcodes within each MSOA or LA.

[8]More formally, this fully controls for the endogenous component of local prices under the assumption that $E[\Delta u_i | \Delta \log P_i, Z_i, \Delta \log \widetilde{RMP}_i] = E[\Delta u_i | v_i, Z_i, \Delta \log \widetilde{RMP}_i] = E[\Delta u_i | v_i] = \zeta v_i$. The second to last equality is satisfied if $(\Delta u_i, v_i)$ is independent of Z_i and $\Delta \widetilde{RMP}_i$. This requires that $\Delta \log \widetilde{RMP}_i$ is uncorrelated with other local demand-side changes (such as local amenity growth) as well as local supply shifters, which is a stricter assumption than 2SLS would require (that our instruments be uncorrelated with supply shifters, Δu_i). The final equality in this expression also requires that the conditional expectation $E[\Delta u_i | v_i]$ be linear, although this can be relaxed by including interactions of v_i with different supply constraints (for example). We show results including these interactions in Appendix A3.

- **Landslide risk.** This is measured using an indicator function for whether a landslide was recorded in an area from 1900-1990.

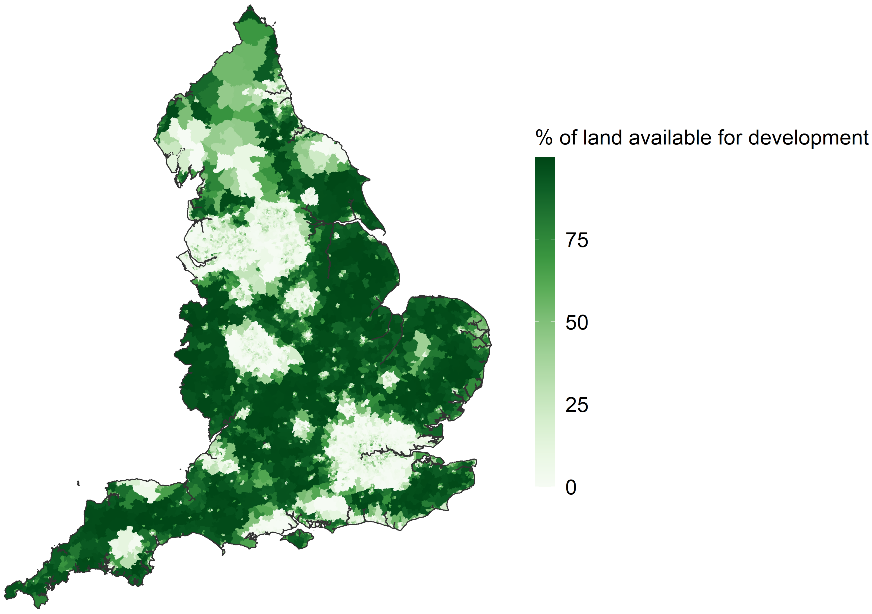
- **Differences in elevation.** This is the maximum minus the minimum elevations averaged across postcodes within each MSOA or LA.

- **Housing density.** This is the number of homes per square kilometre measured in 1993.

- **Share of land available for development.** This is the share of land *not* covered by existing buildings; terrain that is costly to build on (marshes, rocky terrain or bodies of water); and that is not covered by restrictions on development (green belt, national parks or sites of special scientific interest in 1991). We take the inverse hyperbolic sine transformation of share of land available for development ($ArcSinh(1 - \text{share affected by constraints})$). This allows for the impact of constraints on building to be nonlinear: for example, a 1 ppt increase in share of land affected by constraints would decrease the amount of land available for development by 10% in an area where 90% of the land is already subject to constraints, but only decrease it by 2% in an area where 50% of the land was affected by constraints. We use the inverse hyperbolic sine transformation rather than the log transformation, as it is defined at zero (so as not to exclude MSOAs in which are entirely subject to some form of a constraint). Figure 4 shows the proportion of land available for development according to this definition in each MSOA.

- **Historic refusal rates.** These are the share of major projects refused by each local planning authority, taken from Hilber and Vermeulen (2016) over 1979-1990.

Figure 4: Share of land available for development



Note: Land available for development is defined as land area not covered by existing buildings, Green Belt, national parks, sites of special scientific interest, marshes, rocky terrain or bodies of water.

We describe these constraints, including their geographic variation, in more detail in Appendix A1.

We bootstrap standard errors for the control function regressions, to account for the fact that we cluster at the level of local authorities (the unit at which our instrument is defined) and that we must estimate the control function in a first stage. We use the wild-cluster residual bootstrap, as suggested for similar situations in Roodman, MacKinnon, Ørregaard Nielsen, and Webb (2019). This approach adjusts t-statistics and confidence intervals for given standard errors. This is the reason we report the bootstrapped confidence intervals rather than traditional standard errors in our results tables.

4.4 The effects of local supply constraints on housing supply elasticities

Table 3 shows the effects of price, and interactions of price with supply constraints, on housing supply in MSOAs over the period 1996-2021. The interaction terms capture the role of different constraints in explaining local variation in elasticities. In this and subsequent results tables, we demean all our measures of housing constraints. This means that, in each column, the coefficient on the change in the log house price represents the housing elasticity in England over this period for an area with mean values of all the supply constraints. In addition, we standardise all housing constraints such that the coefficient on each price-constraint interaction term represents the effect of a one standard deviation increase in the constraint.

Table 3: Housing supply elasticity MSOA 1996 - 2021: dependent var Δ log Q

	(1) OLS	(2) plus control func.
Δ log P	0.121***	0.073
	[0.092,0.151]	[-0.015,0.144]
Flood risk * Δ log P	-0.001	-0.001
	[-0.005,0.003]	[-0.006,0.004]
Elevation * Δ log P	-0.020***	-0.021***
	[-0.026,-0.014]	[-0.027,-0.016]
Landslides * Δ log P	0.000	0.000
	[-0.002,0.002]	[-0.001,0.003]
Housing density * Δ log P	-0.035***	-0.034***
	[-0.045,-0.025]	[-0.041,-0.022]
Sh. unconstrained * Δ log P	0.021***	0.021***
	[0.014,0.029]	[0.015,0.029]
Refusal rate * Δ log P	-0.003	-0.002
	[-0.010,0.005]	[-0.010,0.005]
Higher degree share	0.002	0.005
	[-0.008,0.013]	[-0.007,0.016]
Elderly share	-0.478***	-0.501***
	[-0.652,-0.303]	[-0.653,-0.290]
Log initial price	0.018	0.027*
	[-0.005,0.042]	[0.005,0.056]
$\hat{v}_i$		0.055
		[-0.078,0.070]
Constant	0.152***	0.215***
	[0.102,0.203]	[0.118,0.325]
R2	0.111	0.111
Observations	6,788	6,788

Notes: Standard errors are clustered at LA level. Supply constraints are standardised so that a unit increase represents a change of one standard deviation. $\Delta LogP$ is the change in quality adjusted house prices. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in 1995. The regressions are also weighted by the number of housing units in each MSOA in 1995.

The results in Table 3 indicate that physical characteristics, flood risk and presence of landslides, have very little influence on elasticities. Elevation is the geographic feature with the largest impact on elasticites with a 1 s.d. increase resulting in a 2.0 ppt fall in the elasticity. As we show in Figure A2 this constraint is relatively geographically concentrated, particularly affecting Northern areas. Historical housing density has the largest influence on the responsiveness of housing supply, with a 1 s.d. rise in the density of an area resulting in a 3.4 ppt fall in the elasticity, indicating that urban areas are less effective at building homes in response to demand changes. A related constraint is the share of land that is unconstrained that accounts for existing development as well as restrictions such as green belt and national parks to provide comprehensive a measure of local land availability. Share of unconstrained land has a slightly smaller but statistically significant and positive impact on elasticities: a 1 s.d. increase in land available boosts elasticities by 2.1 ppt. Historic refusal rates by local planning authorities (a measure of local planning stringency) has only a small effect.[9]

These results are consistent with the broader literature that both uneven topography and land available for development are important drivers of supply elasticity (Saiz, 2010). In England, Hilber and Vermeulen (2016) identified a greater role for regulation relative to geography or land availability. In comparison, we find a small impact of refusal rates over this period. This may be because we incorporate more land-use restrictions in our measure of constrained land including, Green Belt, national parks and sites of special scientific interest (SSSIs).

Appendix Table A8 replicates Table 3 at local authority level. Highly localised constraints such as differences in elevation have less impact on the overall housing supply within local authorities. On the other hand, constraints such as refusal rates, which occur at the level of local planning authorities, do more to constrain housing supply at local authority level than lower levels of geography.

In Appendix A3 we report the interaction effects for the 10 year sub-periods 1996-2006 and 2011-2021. The relative importance of different constraints are broadly similar in the early and late periods. One exception is the role of housing density: the impact of a 1 s.d. increase in density on housing supply is more than twice as large between 2011 and 2021 (-5.8 ppt) compared to the earlier decade (-2.3 ppt). There is also some evidence that the stringency of local planning authorities (proxied by their historic refusal rates) were more important in the later sub-period.

We carry out various sensitivity checks on these results. Table A9 in the Appendix shows results where we: allow for interactions between our constraint measures and the control function (to relax the identification restriction imposed by the control function approach); allow region-specific commute time weights for our measure of residential market penetration alongside regional fixed effects; use the 'residential market access' in place of residential market penetration as our instrument for house price changes (as in Baum-Snow and Han (2024); and exclude control variables for the shares of the population with university education and the shares aged 60 and over in 1991. These alternative specifications all yield very similar estimates.

[9]To identify the most relevant constraints, we applied a LASSO to select only the interaction terms that maximise the model's Bayesian Information Criterion. The LASSO eliminates landslides but selects all the other interaction terms.

4.5 Accounting for housing type and size

So far, we have measured housing supply in terms of the number of residential units. However, it is possible that local prices changes and constraints also impact average house sizes. If the housing market responds to demand surges by creating additional space in existing properties, for instance, converting a loft or garage, this would ease the impacts of low supply responses on the extensive margin. New-built homes may also be larger or smaller depending on local constraints. In Table 4, we explore this by looking at the elasticity of the total number of bedrooms and the stock of different sized homes with respect to price. We run this analysis for the period 2011 to 2021 only, as in earlier years the number of rooms in a large proportion of homes was not recorded in the data.

Columns (1) and (2) show results for number of bedrooms. Supply constraints have a different impact on the number of rooms compared to the number of units: historical housing density and the amount of land available for development have a greater impact on the supply of the number of bedrooms than the number of units.

Columns (3) and (4) show the effect of price changes on the ratio of the stocks of smaller (1 and 2 bed) to larger (3 or more bedroom) properties in areas with different constraints. The most notable differences are the effect of the share of unconstrained land and urban densities on the elasticities of small versus larger homes. Areas with more land available for development tend to build more multi-bedroom homes in response to house price growth and fewer single bedroom homes. In denser and more constrained environments, price increases are associated with a change in the composition of housing which shifts towards smaller properties. This has implications for the types of households who can access different areas, for instance, families with children.

Table 4: Housing supply elasticity by property size, 2011 - 2021

	Number bedrooms		Ratio 1/2 vs 3+ bed	
	(1)	(2)	(3)	(4)
	OLS	plus control func.	OLS	plus control func.
Δ log P	0.032**	-0.014	0.054*	0.272**
	[0.010,0.053]	[-0.080,0.065]	[0.010,0.098]	[0.091,0.360]
Flood risk * Δ log P	-0.005	-0.005	0.018*	0.004
	[-0.010,0.000]	[-0.011,0.001]	[0.001,0.035]	[-0.004,0.008]
Elevation * Δ log P	-0.032***	-0.034***	0.049	-0.018***
	[-0.044,-0.020]	[-0.046,-0.020]	[-0.061,0.159]	[-0.043,-0.025]
Landslides * Δ log P	-0.000	-0.000	-0.003	-0.000
	[-0.007,0.006]	[-0.007,0.006]	[-0.012,0.007]	[-0.001,0.006]
Housing density * Δ log P	-0.058***	-0.057***	0.201	0.028***
	[-0.075,-0.040]	[-0.073,-0.040]	[-0.023,0.425]	[0.022,0.043]
Sh. unconstrained * Δ log P	0.037***	0.036***	0.066	-0.021***
	[0.022,0.051]	[0.021,0.052]	[-0.051,0.183]	[-0.034,-0.017]
Refusal rate * Δ log P	-0.016*	-0.015*	0.102*	0.026**
	[-0.029,-0.004]	[-0.027,-0.002]	[0.019,0.185]	[0.007,0.028]
R2	0.067	0.068	0.125	0.146
Observations	6,788	6,788	6,788	6,788
Controls	Yes	Yes	Yes	Yes

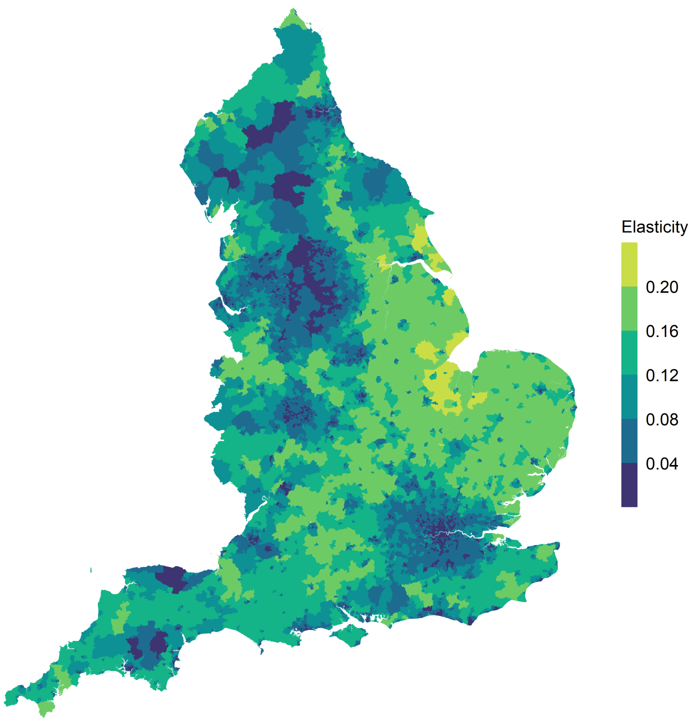
Notes: Standard errors are clustered at LA level. Supply constraints are standardised so that a unit increase represents a change of one standard deviation. $\Delta LogP$ is the change in quality adjusted house prices. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in 2010. The regressions are also weighted by the number of housing units in each MSOA in 2010.

4.6 Local variation in supply elasticities

In this section, we discuss what our results imply for the geographical distribution of elasticities across England. To do so we use information on supply constraints in each MSOA, in combination with the coefficient estimates in Table 3 to calculate a predicted elasticity for each MSOA.

Figure 5 maps the implied elasticities for the period 1996 to 2021. The East of England is the most elastic region, with the majority of areas having an elasticity above 0.15, largely reflecting the amount of flat land available in the region and the absence of Green Belt. Areas of the East Midlands also have more elastic supply, with the highest elasticity of 0.29 in this region. In contrast, the South East and South West of England are much less elastic, particularly around major urban areas such as London and Bristol which are constrained by land availability. Northern England, where the terrain is more mountainous, has large areas of inelastic supply, largely driven by the uneven topography of the land. Pockets of development along the coast are also very inelastic - particularly along the southern coast - reflecting the constraints imposed by existing developments and the coastline. For example, 60% of MSOAs in Brighton and Hove local authority are in the 10% of most inelastic areas. Overall, the interquartile range in elasticities across MSOAs is not great, at 0.05.

Figure 5: Local housing supply elasticities in England, 1996-2021



Notes: Figure shows housing supply elasticities across MSOAs based on the estimates from Column 2 in Table 3.

An important question is how much of the variation in elasticities can be attributed to the different factors we include in our empirical approach. To answer this question, we regress our housing unit elasticities on a constant and each of the supply constraints included in Table 3, omitting differences in elevation. We then carry out an Owen-Shapely decomposition of the resulting R^2, attributing the residual variation to the omitted factor.[10] Table A10 in the Appendix presents the results for the period 1996-2021. Landslides, flood risk and refusal rates account for a negligible share of the variance in elasticities. Share of unconstrained land and housing density explain the vast majority of local variation in elasticities (around 45% and 38% respectively). Differences in elevation account for the remaining 14% of the variance. It is notable that only around 10% of land in England is built up, while almost 40% is protected by natural designation, including greenbelt (Department for Levelling Up, Housing and Communities, 2023). Relative to its land coverage, existing development therefore plays an outsized role in limiting housing supply responses to demand changes.

4.7 Supply constraints and housing affordability

These differences in housing supply constraints across areas also have implications for local housing affordability. One way to quantify the impact of supply restrictions is to measure how they affect house price growth for a given labour demand shock. Table 5 shows results from a regression of log price changes on each area's estimated elasticity, the value of the Bartik labour demand shock (normalised such that each unit increase represents one standard deviation) and their interaction. As one would expect, areas with larger elasticities experience lower price growth, and a given labour demand shock leads to less price growth in areas with fewer constraints.

To give a concrete example using the results from column (2), if boroughs in London had had a supply elasticity that was increased to equal the median elasticity across all England (an increase of 0.046), then price growth over the period 1996-2021 would have been expected to have been lower by 0.05 log points. Actual average price growth in London boroughs was 1.45 log points over this period (0.33 log points greater than the national increase in prices). This translates into a 21 percentage point reduction in average house price growth (which across all London LAs was 330% over this period).

[10]One must be omitted in order to perform the Owen-Shapely decomposition. The results of this decomposition vary depending on which factor is omitted, but we find that our results are not too sensitive to this.

Table 5: Effect of labour demand shocks and elasticities on price changes, 1996 - 2021

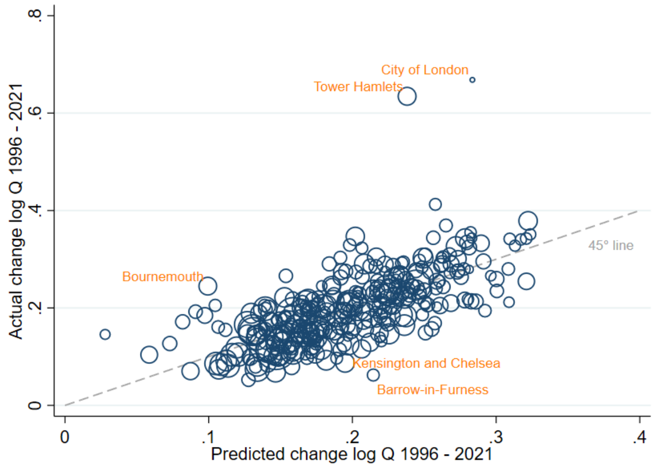
	(1) $\Delta \log P$	(2) $\Delta \log P$
γ	-0.265	-0.043
	(0.183)	(0.214)
$\gamma \times \Delta \log \widetilde{RMP}$	-1.096***	-0.779***
	(0.183)	(0.209)
$\Delta \log \widetilde{RMP}$	0.164***	0.122***
	(0.012)	(0.019)
R2	0.407	0.426
Observations	325	325
Controls	No	Yes

Notes: Column (2) controls are 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices in 1995. $\Delta log\widetilde{RMP}$ is the shift share predicted value of the growth in jobs accessible from each local authority. γ is the estimated elasticity for each local authority. The elasticity is normalised to have mean zero, such that the coefficient on $\Delta \ln \widetilde{RMP}$ gives the effect of labour demand on prices in an area with the average elasticity.

4.8 Residual analysis

A final question we address is which areas increased housing supply more or less than our model would predict. To assess this, we plot the average fitted values from the model used to estimate the results in column (3) of Table 3 within each LA against the actual change in log quantities over the period 1996-2021. This shows that our model has good fit. Areas above the 45 degree line built more houses than we would expect given price growth and supply constraints in each area. Areas below the line built fewer. The City of London and Tower Hamlets, both areas in East London, stand out as having particularly large positive residuals. Tower Hamlets contains areas, including the former London 2012 Olympics site, which have undergone recent regeneration and redevelopment of brownfield sites (GLA (2024)). Other London boroughs, such as Kensington and Chelsea, experienced noticeably lower quantity growth than the regression model would predict, as did Barrow-in-Furness, a largely rural area.

Figure 6: Model fitted and actual change in log housing stocks for different local authorities



Note: Figure shows the average predicted values from housing supply regression taken from column 2 in Table 3 in each LA against actual changes the log housing stock from 1996-2021. The size of the points is proportional to the size of each area's housing stock in 1995.

5 Conclusion

In this paper, we estimate local housing supply elasticities in England. While there were very different price changes across areas over the period 1996 - 2021, we find that this was only to a limited extent reflected in differences in the new supply of new homes. The supply response to demand changes was more limited in areas with more uneven topography, higher density and less land available for development. This latter variable includes the effects of Green Belt designations, which is an important policy constraint on new home building around large cities. We also show that land-use constraints and urban density have larger effects on the supply of bigger properties.

England's relatively weak response of local supply to demand changes has important implications for housing policy. One notable consequence is that, in many areas, demand subsidies or credit subsidies to boost home-ownership are likely to increase prices far more than they increase quantities. In such areas, the gains from demand-side policies are likely to flow disproportionately to existing homeowners.

Our results raise several questions for future research. How might changes in supply constraints affect population movements or sorting of individuals across areas? How do restrictions which affect the construction of different housing types affect family formation and fertility? Answering such questions will require pairing our estimates of supply elasticities with behavioural models of household decision-making.

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Appendix

A1 Details of supply constraint measures

Share of developable land

To measure the amount of land available for development, we use a combination of satellite data on land-cover from 1991 and government maps of locations covered by Green Belt, national parks, sites of special scientific interest, marshes, rocky terrain, bodies of water and existing built-up areas. We define the share of land available for development as one minus the share of land affected by these constraints in 1991.

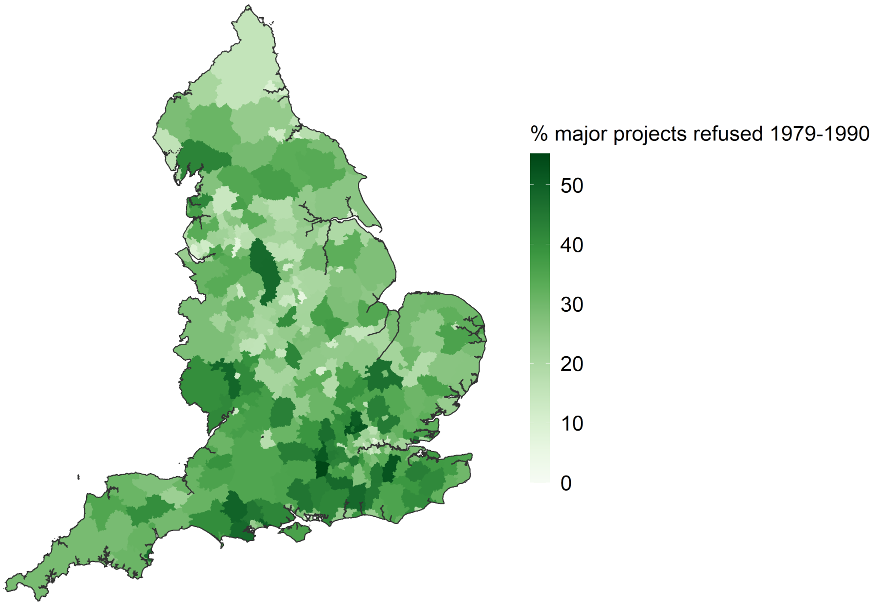
This measure captures both immutable characteristics of areas that act as constraints on development (such as bodies of water) and areas protected in policy from most development (green belt, SSSI and national parks). The coverage of these policy constraints is long-standing and has changed very little over time (for instance, Green Belt boundaries have changed little since the 1970s). We treat it as exogenous.

Refusal rates for residential development

We use historic refusal rates for major residential construction projects to measure the stringency of local planning authorities attitudes to new developments.[11] This is measured in the pre-period 1979 to 1990 to pick up local authorities' historic tendency to reject new projects rather than their contemporary responses to development and land values. Figure A1 shows these refusal rates across LPAs. Historic refusal rates were lower in built-up areas, such as London and Manchester, and tended to be highest in LPAs located in the London Green Belt and other countryside areas.

[11] Annual data on local refusal rates were kindly provided to us by Christian Hilber. Average refusal rates for 1979-2008 were used to measure the restrictiveness of local planning authorties in Hilber and Vermeulen (2016).

Figure A1: Refusal rates for major residential construction projects, 1979-1990



Note: These data were originally used to measure the strictness of local planning rules in Hilber and Vermeulen (2016). Original source is the Department for Communities and Local Government.

Differences in elevation, landslides and flood risk

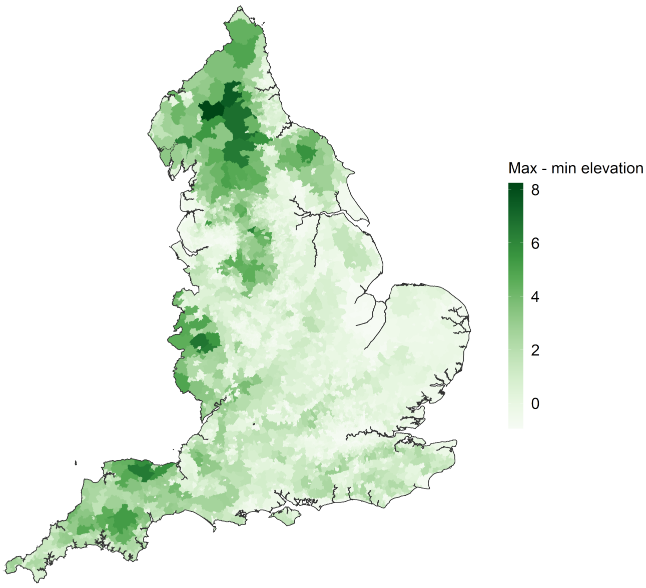
We incorporate data on terrain that is more costly to develop such as uneven topography (differences in elevation) and land at risk of geohazards - for instance, properties built in areas prone to flooding or landslides require additional design features to mitigate the risk of damage.

We obtain data on slopes from the Ordnance Survey OS Terrain 50 database. We use the difference between the maximum and minimum elevations across postcodes within each MSOA to measure local topographic constraints to construction. Figure A2 displays this measure for England. Areas of steep slopes are largely concentrated in areas of the West, South West and Northern England. East England is by contrast relatively flat.

We take data for local landslides from the British Geological Survey's Landslide Database. A landslide is defined as "a mass of soil, rock or debris that has moved, or is still in the process of moving, down slope" British Geological Survey (2022). The landslide database is a geocoded list of recorded landslides compiled from media reports, geological maps and historical accounts over the last several centuries (although naturally the coverage of the database has improved considerably in more recent years). We use a dummy variable for MSOAs which have experienced a landslide between 1900-1990 to measure local landslide risk.

We obtain measures of flood risk from the Environmental Agency which records the

Figure A2: Topographic constraints



Note: Figure shows the maximum minus minimum elevation across postcodes with each MSOA.

likelihood of flooding (very low, low, medium, and high [12]) from rivers and/or the sea at postcode-level. We take the median likelihood of flooding across postcodes within each MSOA to measure local flood risk. This particularly affects coastal areas, including Cornwall and the east coast, as well as low-lying areas (such as Somerset) and areas located near rivers (Yorkshire, for instance).

A2 Details of instrument construction

A2.1 Data

Labour market data: We obtain data on employment in different local authorities at the industry level from various sources. For earlier years, we use data from the Annual Employment Survey (AES) (previously the Census of Employment) which was a survey of employees conducted between 1991 and 1998. Industries are defined at the two-digit Standard Industry Classification (1992) level.

For later years (2007 onwards) we use data from the Annual Business Inquiry (ABI) and Business Register and Employment Survey (BRES), which are both large-scale employer surveys. The industries we use for this period are two-digit SIC 2007.

Initial industry shares for the instrument are taken from 1991 and 2007 for periods 1996 - 2006 and 2011 - 2021, respectively. For analysis over the period 1996-2021 we use 1991 initial industry shares and convert 1992 SIC industries into 2007 codes using a lookup constructed

[12] Areas designated as very low, low, medium and high flood risk have likelihoods of flooding below 0.1%, 0.1% - 1%, 1% - 3.3% and above 3.3%, respectively.

by Jennifer Smith at https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/direct/.

We obtain information on the number of workers *resident* in each location from the Labour Force Survey (for the years 1994-2003) and annual population survey from (for the years 2004-2021). All datasets are accessed via Nomis website.[13]

Commutes and travel times: We use data on commute flows and travel times across local authorities from the National Travel Survey (NTS, Department for Transport (2022)). The data contains information on journeys taken by respondents over a 7-day period, recording the purpose of the journey, the mode of transport and time taken at each stage, and origins and destinations. We use special licence data which reports origins and destinations at the level of local authorities.

In each year, the NTS includes around 7,000 households; we pool years 2007 to 2015. For pairs of local authorities for which no commutes are observed, we impute commute times using (scaled) travel times for non-commuters. For remaining pairs of local authorities with completely missing journey information (around 2%), we impute based on distance. We match the vast majority of commute flows reflected in the 2011 Census.

Local area characteristics: We compile a number of local area demographic and economic characteristics to include as controls in our regressions. We use data from the 1991 Census and ONS population data for 1995 to construct the share of residents with a higher degree across MSOAs and share of residents aged over 60 for local authorities, respectively.

Gravity model of commuting

Our instrument is constructed by aggregating labour demand shocks across commuting destinations, with weights recovered from a gravity model of commuting.

We estimate:

$$\ln \pi_{ij} = a_i + b_j - \omega \tau_{ij} \tag{8}$$

where π_{ij} is the commute flow between origin local authority i and destination local authority j, a_i and b_j are origin and destination fixed effects, respectively, and τ_{ij} is travel time. ω then represents the responsiveness of commute flows to travel time: higher values of ω indicate a higher disutility from commute time.

Equation 8 is estimated via Poisson Maximum Liklihood which has been shown to outperform OLS in the presence of heteroskedacity (Silva and Tenreyro (2006)). In robustness

[13] https://www.nomisweb.co.uk/

checks, we estimate separately for each commuting region.

A2.2 Alternative Residential Market Access Measure

Baum-Snow and Han (2024) define residential market access, a measure consistent with a spatial model of choices over neighbourhoods and commute destinations.

The measure if similar to the RMP measure we use, but is weighted to reflect the degree of competition workers face from other commuters in possible commute destinations. The degree of competition is measured by firm market access.

Calculating for residential and firm market access requires finding the fixed point that solves the following system of equations.

$$RMA_{i,t} = \sum_j \frac{L_{j,t} e^{-\omega \tau_{ij}}}{FMA_{j,t}} \tag{9}$$

and

$$FMA_{j,t} = \sum_i \frac{\pi_{i,t} e^{-\omega \tau_{ij}}}{RMA_{i,t}} \tag{10}$$

where $\pi_{i,t}$ is the population of workers living in area i in year t.

Following Baum-Snow and Han (2024) we make use of shift-share predictions of RMA and FMA. In practice this means solving for vectors of $\widetilde{RMA}_{i,t}$ and $\widetilde{FMA}_{j,t}$ defined by

$$\widetilde{RMA}_{i,t} = \sum_j \frac{\tilde{L}_{j,t} e^{-\omega \tau_{ij}}}{\widetilde{FMA}_{j,t}} \tag{11}$$

and

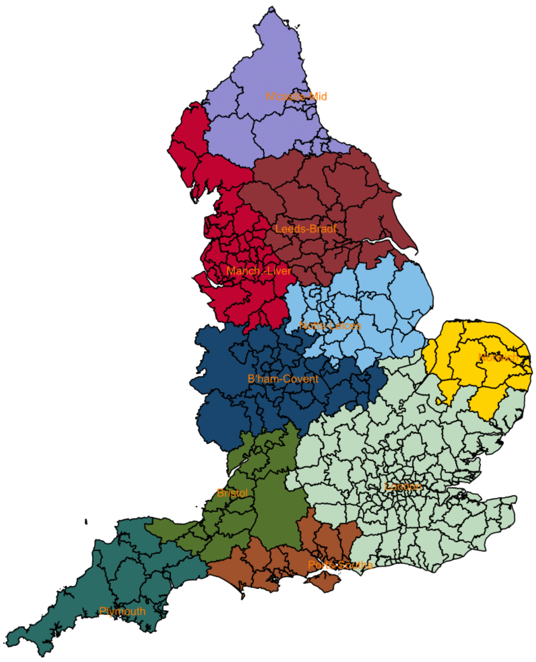
$$\widetilde{FMA}_{j,t} = \sum_i \frac{\pi_{i,t_0} e^{-\omega \tau_{ij}}}{\widetilde{RMA}_{i,t}} \tag{12}$$

In practice, we calculate these objects within regions (solving for the fixed point is difficult across all 325 local authorities). We allow ω, the weights on commute times to each destination, to vary within regions.

We hold population shares in each region constant at their values in the base year for these calculations (that is, we use π_{i,t_0} in the expression for $\widetilde{FMA}_{j,t}$ rather than $\pi_{i,t}$), effectively imposing uniform population growth. We can then instrument for changes in local house prices using $\Delta \log \widetilde{RMA}_{i,t}$ (differenced over the same period as house prices).

Construcing "metro" regions We calculate RMA within city regions designed to approximate labour markets (in which it is approximately true that those working in each area, also live there). We construct our own measures as existing Travel to Work Areas (the UK equivalent of American Commuting Zones) are too small for our purposes, and many workers commute across TTWAs (for example, Richmond a suburb in London is classed as a separate TTWA from central London). To produce our own 'metro regions', we start by taking the top five cities in terms of number of jobs obtained from Centre for Cities (2015). After combining nearby cities (for instance, Manchester and Liverpool) we then assign each local authority to the city where the biggest share of workers commute according to the 2011 census. For unassigned areas, those bordering existing metro regions are assigned to that area, while we create new metro regions for unassigned local authorities that are clustered together. This process results in 10 metro areas which are self-contained and reflect real-world commuting patterns. Figure A3 shows these metro regions on the map.

Figure A3: English metro-regions



Note: Metro-regions constructed based on commute flows from census 2011.

Regional gravity model estimates Table A1 reports the coefficient on travel time from regressions of commute flows on travel times with origin and destination fixed effects with in each metro-region. We use these as weights in our RMA calculations. The coefficient on commute time is negative in all metro-regions, indicating commutes with longer travel times are made less frequently. There are substantial differences across regions in the sensitivity of commute flows to travel times. The magnitude of the coefficient for London, for instance, is roughly half that for Newcastle-Middlesborough, implying Newcastle-Middlesborough commuters are around twice as responsive to a given rise in travel time compared to commuters in London. In other words, workers in London are willing to travel further for jobs than workers in Newcastle-Middlesborough.

Table A1: Gravity model

Birmingham-Coventry		
	-0.107***	(0.0033)
Bristol		
	-0.100***	(0.0044)
Leeds-Bradford-Sheffield		
	-0.106***	(0.0043)
London		
	-0.065***	(0.0013)
Manchester-Liverpool		
	-0.117***	(0.0038)
Newcastle-Middlesborough		
	-0.121***	(0.0061)
Norwich		
	-0.093***	(0.0051)
Nottingham-Leicester		
	-0.110***	(0.0048)
Plymouth		
	-0.084***	(0.0134)
Portsmouth-Southampton		
	-0.090***	(0.0047)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The first column shows coefficients on travel times from Poisson Pseudo Maximum Likelihood (PPML) regressions of commute flows between local authorities on average travel times estimated using the National Travel Survey between 2007 and 2015 including origin and destination fixed effects. The second column reports standard errors in parentheses. Regressions are run separately by metro-region (defined in the text).

A3 Supplementary Tables

Table A2: First stage MSOA-level: dependent var Δ log P

	(1) 1996-2006	(2) 2011-2021	(3) 1996-2021
Δ log $\widetilde{RMP}$	1.417***	4.008***	2.364***
	(0.293)	(0.493)	(0.320)
Higher degree share	0.019*	-0.018	0.033*
	(0.009)	(0.011)	(0.015)
Elderly share	-0.009	-0.120	-0.699*
	(0.222)	(0.179)	(0.350)
Log initial price	-0.116***	-0.009	0.002
	(0.024)	(0.018)	(0.044)
Constant	0.925***	0.315***	1.255***
	(0.046)	(0.041)	(0.075)
R2	0.109	0.152	0.336
Observations	6,788	6,788	6,788
F-stat	23.34	65.99	54.67

Notes: Standard errors clustered at LA level. House prices are quality adjusted. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in the year prior to the start of each growth period. Regressions are also weighted by number of housing units in each area in that year.

Table A3: First stage LAD-level: dependent var Δ log P

	(1) 1996-2006	(2) 2011-2021	(3) 1996-2021
Δ log $\widetilde{RMP}$	1.116**	1.995**	1.680***
	(0.342)	(0.719)	(0.406)
Higher degree share	0.003	-0.037*	-0.003
	(0.010)	(0.016)	(0.019)
Elderly share	0.148	-0.282	-0.459
	(0.229)	(0.200)	(0.365)
Log initial price	-0.046	0.089*	0.187*
	(0.043)	(0.037)	(0.085)
Constant	0.946***	0.335***	1.363***
	(0.046)	(0.045)	(0.085)
R2	0.129	0.259	0.445
Observations	325	325	325
F-stat	10.62	7.71	17.13

Notes: House prices are quality adjusted. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in the year prior to the start of each growth period. Regressions are also weighted by number of housing units in each area in that year.

Table A4: Alternative instruments: first stage MSOA-level

	1996-2006		2011-2021		1996-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
	RMP	Bartik	RMP	Bartik	RMP	Bartik
Δ log $\widetilde{RMP}$	1.417***	0.667***	4.008***	0.903**	2.364***	0.983***
	(0.293)	(0.129)	(0.493)	(0.313)	(0.320)	(0.204)
Higher degree share	0.019*	0.018	-0.018	-0.015	0.033*	0.033
	(0.009)	(0.009)	(0.011)	(0.010)	(0.015)	(0.017)
Elderly share	-0.009	-0.108	-0.120	-0.596***	-0.699*	-1.036**
	(0.222)	(0.220)	(0.179)	(0.169)	(0.350)	(0.399)
Log initial price	-0.116***	-0.081***	-0.009	0.053**	0.002	0.109**
	(0.024)	(0.021)	(0.018)	(0.018)	(0.044)	(0.040)
Constant	0.925***	0.851***	0.315***	0.270***	1.255***	1.074***
	(0.046)	(0.048)	(0.041)	(0.063)	(0.075)	(0.096)
R2	0.109	0.072	0.152	0.098	0.336	0.266
Observations	6,788	6,788	6,788	6,788	6,788	6,788
F-stat	23.34	26.70	65.99	8.34	54.67	23.15

Notes: Standard errors clustered at LA level. House prices are quality adjusted. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in the year prior to the start of each growth period. Regressions are also weighted by number of housing units in each area in that year.

Table A5: Alternative instruments: first stage LAD-level

	1996-2006		2011-2021		1996-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
	RMP	Bartik	RMP	Bartik	RMP	Bartik
Δ log $\widetilde{RMP}$	1.116**	0.517***	1.995**	0.360	1.680***	0.580*
	(0.342)	(0.148)	(0.719)	(0.332)	(0.406)	(0.241)
Higher degree share	0.003	-0.005	-0.037*	-0.042*	-0.003	-0.020
	(0.010)	(0.010)	(0.016)	(0.016)	(0.019)	(0.020)
Elderly share	0.148	0.092	-0.282	-0.517**	-0.459	-0.588
	(0.229)	(0.221)	(0.200)	(0.165)	(0.365)	(0.406)
Log initial price	-0.046	0.004	0.089*	0.138***	0.187*	0.339***
	(0.043)	(0.035)	(0.037)	(0.028)	(0.085)	(0.071)
Constant	0.946***	0.907***	0.335***	0.326***	1.363***	1.319***
	(0.046)	(0.055)	(0.045)	(0.063)	(0.085)	(0.120)
R2	0.129	0.095	0.259	0.243	0.445	0.408
Observations	325	325	325	325	325	325
F-stat	10.62	12.18	7.71	1.18	17.13	5.79

Notes: House prices are quality adjusted. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in the year prior to the start of each growth period. Regressions are also weighted by number of housing units in each area in that year.

Table A6: Housing supply elasticity MSOA 1996 - 2006: dependent var Δ log Q

	(1) OLS	(2) plus control func.
Δ log P	0.093***	-0.045
	[0.064,0.122]	[-0.149,0.061]
Flood risk * Δ log P	0.000	0.001
	[-0.002,0.002]	[-0.001,0.003]
Elevation * Δ log P	-0.011***	-0.012***
	[-0.014,-0.007]	[-0.016,-0.009]
Landslides * Δ log P	0.000	0.000
	[-0.001,0.001]	[-0.001,0.001]
Housing density * Δ log P	-0.021***	-0.020***
	[-0.026,-0.015]	[-0.026,-0.016]
Sh. unconstrained * Δ log P	0.011***	0.012***
	[0.008,0.015]	[0.008,0.015]
Refusal rate * Δ log P	0.001	0.002
	[-0.003,0.005]	[-0.001,0.007]
Higher degree share	-0.004	0.000
	[-0.010,0.002]	[-0.006,0.008]
Elderly share	-0.166***	-0.146**
	[-0.252,-0.080]	[-0.278,-0.035]
Log initial price	0.030***	0.022**
	[0.016,0.044]	[0.007,0.036]
$\hat{v}_i$		0.150***
		[0.107,0.274]
Constant	0.034	0.162***
	[-0.001,0.069]	[0.070,0.258]
R2	0.099	0.102
Observations	6,788	6,788

Notes: Standard errors clustered at LA level. Supply constraints are standardised. House prices are quality adjusted. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in 1995. The regressions are also weighted by number of housing units in each area in 1995.

Table A7: Housing supply elasticity MSOA 2011 - 2021: dependent var Δ log Q

	(1) OLS	(2) plus control func.
Δ log P	0.059***	0.025
	[0.036,0.082]	[-0.059,0.097]
Flood risk * Δ log P	-0.004	-0.004
	[-0.011,0.002]	[-0.012,0.002]
Elevation * Δ log P	-0.040***	-0.041***
	[-0.053,-0.027]	[-0.059,-0.029]
Landslides * Δ log P	0.000	0.000
	[-0.006,0.006]	[-0.006,0.006]
Housing density * Δ log P	-0.059***	-0.058***
	[-0.080,-0.038]	[-0.078,-0.037]
Sh. unconstrained * Δ log P	0.021*	0.021*
	[0.004,0.039]	[0.002,0.039]
Refusal rate * Δ log P	-0.017*	-0.016*
	[-0.032,-0.003]	[-0.033,-0.003]
Higher degree share	-0.000	-0.001
	[-0.008,0.007]	[-0.010,0.008]
Elderly share	-0.256***	-0.278***
	[-0.346,-0.167]	[-0.380,-0.158]
Log initial price	0.020***	0.022**
	[0.009,0.031]	[0.010,0.036]
$\hat{v}_i$		0.036
		[-0.067,0.092]
Constant	0.111***	0.124***
	[0.089,0.133]	[0.085,0.163]
R2	0.063	0.063
Observations	6,788	6,788

Notes: Standard errors clustered at LA level. Supply constraints are standardised. House prices are quality adjusted. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in 2010. Regressions weighted by number of housing units in each area in 2010.

Table A8: Housing supply elasticity LAD 1996 - 2021: dependent var Δ log Q

	(1) OLS	(2) plus control func.
Δ log P	0.159***	0.231*
	[0.118,0.199]	[0.013,0.304]
Flood risk * Δ log P	-0.003	-0.003***
	[-0.008,0.002]	[-0.019,-0.004]
Elevation * Δ log P	-0.007*	-0.006***
	[-0.013,-0.000]	[-0.019,-0.008]
Landslides * Δ log P	0.001	0.002*
	[-0.004,0.007]	[0.001,0.010]
Housing density * Δ log P	-0.022***	-0.023**
	[-0.033,-0.011]	[-0.022,-0.005]
Sh. unconstrained * Δ log P	0.028***	0.027***
	[0.020,0.036]	[0.029,0.041]
Refusal rate * Δ log P	-0.010	-0.010*
	[-0.020,0.001]	[-0.020,-0.002]
Higher degree share	0.006	0.007
	[-0.007,0.018]	[-0.005,0.017]
Elderly share	-0.741***	-0.731***
	[-0.960,-0.521]	[-0.905,-0.466]
Log initial price	0.005	-0.022
	[-0.036,0.047]	[-0.063,0.053]
$\hat{v}_i$		-0.076***
		[-0.282,-0.082]
Constant	0.177***	0.074
	[0.106,0.249]	[-0.042,0.341]
R2	0.487	0.489
Observations	325	325

Notes: Supply constraints are standardised so that a unit increase represents a change of one standard deviation. $\Delta LogP$ is the change in quality adjusted house prices. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each LA in 1995. Regressions are also weighted by number of housing units in each LA in 1995.

Table A9: Alternative specifications: MSOA housing supply elasticity 1996 - 2021

	(1) CF interactions	(2) region commutes	(3) RMA; region commutes	(4) no controls
Δ log P	0.041	0.087	0.087	0.066
	[-0.047,0.116]	[-0.061,0.212]	[-0.123,0.289]	[-0.018,0.133]
Flood risk * Δ log P	-0.000	-0.002	-0.002	-0.001
	[-0.004,0.004]	[-0.007,0.003]	[-0.008,0.003]	[-0.006,0.003]
Elevation * Δ log P	-0.021***	-0.026***	-0.026***	-0.022***
	[-0.027,-0.016]	[-0.031,-0.019]	[-0.031,-0.019]	[-0.028,-0.017]
Landslides * Δ log P	0.001	-0.000	-0.000	-0.001
	[-0.001,0.004]	[-0.002,0.003]	[-0.002,0.003]	[-0.003,0.002]
Housing density * Δ log P	-0.035***	-0.038***	-0.038***	-0.031***
	[-0.043,-0.025]	[-0.046,-0.027]	[-0.046,-0.027]	[-0.038,-0.019]
Sh. unconstrained * Δ log P	0.023***	0.019***	0.019***	0.021***
	[0.017,0.031]	[0.010,0.024]	[0.010,0.024]	[0.015,0.029]
Refusal rate * Δ log P	-0.002	-0.002	-0.002	-0.005
	[-0.010,0.005]	[-0.014,0.001]	[-0.014,0.001]	[-0.014,0.002]
Log initial price	0.034**	0.022	0.022	0.044**
	[0.010,0.062]	[-0.001,0.048]	[-0.002,0.049]	[0.020,0.074]
Constant	0.243***	0.237**	0.237	0.136**
	[0.142,0.353]	[0.072,0.415]	[-0.028,0.485]	[0.051,0.243]
R2	0.122	0.120	0.120	0.104
Observations	6,788	6,788	6,788	6,788
F-stat	54.67	24.11	13.27	56.91
b				

Notes: Standard errors are clustered at LA level. Supply constraints are standardised so that a unit increase represents a change of one standard deviation. $\Delta LogP$ is the change in quality adjusted house prices. Housing density and share unconstrained are log and inverse hyperbolic sine transformed, respectively. Regressions control for 1991 population shares of those with university education and those aged 60 in each local authority, as well as log house prices for each MSOA in 1995. Regressions are also weighted by number of housing units in each MSOA in 1995.

Table A10: Share of variance in local price elasticities explained by constraints

	Owen-Shapely (%)
Flood risk	0
Landslides	0
Housing density	38
Share unconstrained	45
Refusal rate	2
Elevation	14

A4 Linearised instrument and Rotemberg weights

Our reduced form is to regress housing supply on

$$\widetilde{RMP}_{i,t} = \sum_j \tilde{L}_{j,t} e^{-\epsilon\kappa\tau_{ij}} \tag{13}$$

So

$$\Delta \ln Q_i = \beta \Delta \ln \widetilde{RMP}_i + \theta X_i + \epsilon_i \tag{14}$$

Use the Frisch-Waugh-Lowell theorem to partial out the effects of X_i

$$\Delta \ln Q_i^{\perp} = \beta \Delta \ln \widetilde{RMA}_i^{\perp} + \epsilon_i^{\perp} \tag{15}$$

Now we want to decompose $\Delta \ln \widetilde{RMP}_i$ into shifts and shares.

Take a first order taylor expansion around $\widetilde{RMP}_{i,0}$

$$\ln \widetilde{RMP}_{i,t} - \ln \widetilde{RMP}_{i,0} \approx \frac{1}{\widetilde{RMP}_{i,0}} \sum_k \sum_j E_{jk,t_0} \times e^{-\kappa\tau_{ij}} \times \left(\frac{E_{k,t}^{-j} - E_{k,0}^{-j}}{E_{k,t_0}^{-j}} \right) \tag{16}$$

Rewrite this as

$$\ln \widetilde{RMP}_{i,t} - \ln \widetilde{RMP}_{i,0} \approx \sum_k \sum_j Z_{jki} \times g_{k,t}^{-j} \tag{17}$$

Here $Z_{jki} = E_{jk,t_0} \times e^{-\kappa\tau_{ij}}$ is a function of employment shares in area j and industry k (and their distance to area i), and $g_{k,t}^{-j} = \left(\frac{E_{k,t}^{-j} - E_{k,0}^{-j}}{E_{k,t_0}^{-j}} \right)$. This is now an additive combination of 'shifts' and 'shares' allowing us to apply results applying to more standard linear shift share instruments.

Using this linearised instrument, we obtain a coefficient of 0.137 (standard error 0.067) for the 2SLS regression of the change in log quantity on the change log price across LAs for the period 1996-2021. This is very similar to the coefficient of 0.142 that we obtain in the analogous regression in Table 1.

Goldsmith-Pinkham et al. (2020) show that we can decompose the reduced form coefficient β of a shift-share instrument $B_i = \sum_k Z_{ik} g_k$ regressed on some outcome Y into

$$\beta = \sum_k \alpha_k \beta_k$$

where

Table A11: Negative and positive weights

	Sum	Mean	Share	N
Negative	-0.220	-0.004	0.381	35
Positive	0.357	0.010	0.619	49

$$\alpha_k = \frac{g_k Z_k' B^{\perp}}{\sum_{k'} g_{k'} Z_{k'}' B^{\perp}}$$

and

$$\beta_k = \left(Z_k' B^{\perp}\right)^{-1} \left(Z_k' Y^{\perp}\right)$$

In our case

$$\beta \approx \sum_j \sum_k \alpha_{jk} \beta_{jk}$$

where

$$\alpha_{jk} = \frac{g_k^{-j} Z_{jk}' \Delta \ln \widetilde{RMP}^{\perp}}{\sum_{jk'} g_{k'}^{-j} Z_{jk'}' \Delta \ln \widetilde{RMP}^{\perp}}$$

and

$$\beta_{jk} = \left(Z_{jk}' \Delta \ln \widetilde{RMP}^{\perp}\right)^{-1} \left(Z_{jk}' \Delta \ln Q_i^{\perp}\right)$$

By summing the weights for alpha across areas, we can calculate Rotemberg weights for industries, $\alpha_k = \sum_j \alpha_{jk}$.

Table A11 shows the sum of positive and negative weights across industries, the average weight for each industry and their shares in the total sum of absolute Rotemberg weights. 35 industries have negative weights and 49 have positive weights.

The industries with the largest Rotemberg weights, for the regression analogous to that shown in Table 1 are shown in Table A12. Taken together, these industries account for 38% of the sum of the positive weights.

Goldsmith-Pinkham et al. (2020) recommend checking to see if the shares of the industries with the largest Rotemberg weights are correlated with possible confounders. Table A13 shows the correlations between industry shares in different local authorities and changes in local refusal rates for major developments from 1996-2008, a proxy for changes to the strictness of local planning policy. The estimated correlations are low, suggesting that this poses little threat to identification.

Table A12: Top 5 Rotemberg weight industries

Industry	$\hat{\alpha}_k$
Activities auxiliary to financial services	0.066
Crop and animal production	0.052
Manufacture of fabricated metal products	0.031
Food and beverage services	0.030
Computer programming	0.029
Total	0.209
Share of positive weights	0.384

Table A13: Correlation between local industry shares and changes in local refusal rates for major projects

Industry	Correlation
Activities auxiliary to financial services	0.041
Crop and animal production	-0.087
Manufacture of fabricated metal products	0.098
Food and beverage services	-0.131
Computer programming	0.036