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Housing Affordability: Is New Local Supply the Key?

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Housing affordability: is new local supply the key?

Abstract: *This paper seeks to predict the impact of future housing supply on the affordability of residential space in the United Kingdom, using quantitative model-based simulation methods. Our spatially disaggregated analysis focuses on the greater South East region, approximately within 1.5 hours commuting time from central London. A dynamic spatial panel model is applied to account for observed temporal variations in property prices and housing affordability across districts. The dynamic structure of this model allows us to assess the scale and extent of knock-on effects of local supply shocks in one district on other districts in the region. These complex spatial effects have been largely ignored in local or regional housing market forecasting models to date. Applying this model, we are able to demonstrate that local house prices and affordability are not only determined by the underlying supply and demand conditions in the market in question but also depends crucially on conditions in neighbouring housing markets whose properties can be considered close substitutes within a larger regional housing market. We also show that increasing housing supply in the most critical areas has little impact on (both local and regional) affordability even if wages do not change in response to an increase in employment.*

Keywords: *Local supply shocks, dynamic spatial panel analysis, housing affordability, house price forecasts*

1. Introduction

Although there is no consensus on the causes of unaffordable housing or even whether its existence prove that markets are imperfect, the detrimental social and financial impact to the large number of individuals and households negatively affected by it are virtually undisputed. In the US, government and business leaders struggle to agree on strategies for combating the issue (Glaeser and Gyourko 2003) while in the UK, the principal government policy is to increase the supply of housing in key areas to improve affordability. This simple approach is based on the fundamental assumption that increasing supply would reduce prices. However, Crook et al. (2010) show that providing new homes in the most critical areas seems to have little effect on affordability. Although, Glaeser et al. (2006) argue that this may be due to higher wages offered to new residents, we show that even with exogenous wages new supply has a very small effect on local affordability.

This paper explores how dynamic spatial panel data modelling and simulation methodology can be used to assess the extent to which new housing stock makes housing more affordable, following the work of Meen et al. (2005) and Fingleton (2008) in particular. The approach is somewhat different from the complex modelling carried out by Meen et al (2005), and more in line with the simpler approach of Fingleton (2008), which allows an element of theoretical coherence throughout. Although there are alternatives that have been suggested in the literature, we measure affordability simply as the ratio of house prices to mean annual wage levels. Other measures include the median house price to median income ratio, which can be adapted to focus on access to housing by using the lowest quartile house price to lowest quartile income ratio, or the proportion of households that can only afford acceptable accommodation with assistance[1]. However, the price to wage ratio is easy to implement and is the measure that has captured the attention of politicians[2]. It is also commonly used to examine the wider impact of housing affordability. For example, there is an important environmental aspect to the issue of affordability since, if housing is largely unaffordable where people work, high volumes of commuting are likely to occur (Sultana 2002).

The focus of the analysis is the South East of England where lack of affordability is probably at its most acute in the UK. This includes Central London which is the major centre of employment and has house prices that are the highest in the country. As in many great cities, daily ebb and flow of commuters from more affordable locations to employment centres has a costly financial impact on individual households and on local and global environments (Tse and Chan 2003). There are also additional macroeconomic and regional economic issues because relatively low affordability in a core region with a high level of labour demand will inhibit the inward mobility of labour. Naturally, this leads to feedback effects between house prices and local economies and other endogenous processes that influence them simultaneously. Our estimation approach adjusts for using a first difference model and instrumenting supply and demand indicators with their lagged values. We test the validity of our estimates and the contribution of individual factors to price changes using on-step ahead predictions. The results show that spatial and temporal lags are critical to increasing forecasting accuracy.

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[1] http://www.communities.gov.uk/publications/housing/affordabilitytargetsimplications

[2] 'ten years ago house prices were 3.5 times people's annual salary' now 'house prices are 6 times annual salary', speech delivered by the Rt. Hon. John Prescott (The then Deputy Prime Minister) on 1st April 2005.

One of the suggested solutions to housing affordability issues is increasing local supply in the most problematic areas (Meen et al. 2005). The fundamental economic logic dictates that increasing supply should reduce prices. However, in the context of complex interaction effects between commutable areas caused by commuting flow patterns it is difficult to easily quantify the impact of new supply on house prices and their affordability. The overall impact depends not only on income but also on income elasticity of demand in the area where supply increases. In fact, many studies show that increasing housing supply may eventually lead to rising demand (Szumilo et al. 2017; Ball et al 2010; Fingleton 2008). The objective of this study is to examine if new local supplies of dwellings can improve housing affordability both within the growing location and in the region. To this aim, we develop a model of house prices that allows affordability to react differently to changes in wages and employment. By assuming that wages are exogenous but allowing employment to depend on housing supply we show how new housing may lead to lower affordability. Since allowing workers to travel between districts leads to demand interactions between locations, we also allow for a spatial effect in prices. Our estimation approach is based on a reduced form equation which allows us to simulate the impact of new supply on affordability ratios. The advantage of this approach is that, unlike interpreting model coefficients, it allows one to quantify not only the magnitude but also spatial distribution of the impact of new supply on affordability. Empirical predictions are made for a hypothetical increase in housing stock of 5% and 15% in each of London’s 32 Boroughs. We also examine Cheshire’s (2014) suggestion that building 1.6m houses on London’s greenbelt would make housing more affordable. We analyse two different versions of our empirical predictions assuming that increased supply either interacts with demand or has no effect on it. Overall, supply is found to have a much smaller effect on affordability than expected. Furthermore, it appears that even if supply is increased in all areas by an equal margin, the impact on prices would not be distributed evenly across space.

Section 2 reviews different definitions of affordability and the economic significance of the concept. Section 3 summarizes our data. Section 4 presents the rationale behind the research question and the economic logic that leads to it. Section 5 discusses our estimation methods. Section 6 presents our empirical predictions and section 7 concludes.

2. Defining housing affordability

Despite the fact that its analytical definition has evolved over the last two decades, affordability remains an elusive concept (Stone 2006). In fact, designing an affordability policy is hampered by the lack of a commonly accepted definition. Reducing house prices appears to be a recurring recommendation of many researchers (Bramley, 1994; Hilber, 2016) but measuring the impact of this approach requires a sound definition of affordability as well as an understanding of the market mechanisms underlying house price formation.

The concept of affordability

The definition of affordability adopted in this article is simply the ratio of house prices to wages. However, several other metrics have been proposed in the literature. Stone (2006) alludes to four types of affordability: relative, subjective, budget-standards-based and residual-income-based. Although they are conceptually very similar, small differences make each class appropriate for different applications.

Relative affordability refers to changes in the relationship between summary measures of house prices or costs and household incomes. At its core, this is a form of the price/wage ratio approach that allows one to focus more on affordability to potential house buyers. This approach is clearly useful to lenders who focus on transactions but offers little information about affordability from the perspective of house owners.

Subjective affordability is based on market efficiency and the assumption that all households make rational decisions. In this context, all houses are occupied by people who have decided that they can afford it. Consequently, it makes little sense to define housing affordability as in efficient markets all households would sort themselves only into dwellings they can afford. However, as Stone (2006) points out, there is a considerable difference in the discretion of income allocation to housing costs versus other costs between high and low income households. This means that the subjective experience of affordability of housing between the two would differ considerably.

The family budget standards approach to housing affordability is based on an analysis of different measures of how much of it should be dedicated to housing costs. If a monetary amount necessary to achieve a certain standard of living is determined (for example the poverty threshold Bernstein et al. 2000), then the minimum income required to support a household in a certain area can be established. In the context of housing, this is very similar to the price/wage ratio approach as the two must stay in a certain relation to each other to ensure that households are not pushed into poverty. However, while the approach works well for perishable homogenous goods, it is difficult to establish universal poverty thresholds for housing. Even if physical standards could be established, the corresponding monetary amount would be very difficult to find (see Stone 2006 for more details).

The residual income approach adopts a slightly different perspective on disposable income and recognises that housing costs are one of the largest and least flexible items in household budgets. This means that income adequacy should not be defined by its overall level but by the amount left after paying for adequate housing. This controls for different sizes and types of households which, with the same level of disposable income, may require different amounts for non-shelter goods. Although this may be the most comprehensive indicator of affordability, its practical application requires defining a standard level of income that would be considered as adequate for non-housing goods. As this benchmark is likely to change over space and time the residual approach cannot be universally applied.

The idea that housing cost should not exceed a certain proportion of household income is common to all of these metrics. This allows the ratio approach to be a useful metric as the proportion of the budget taken up by housing costs can be changed by variations in either (or both) of the two variables. While the residual approach may be the most comprehensive, the focus of this study is on measuring changes of affordability over time and comparing them across different locations, rather than against a general benchmark. We do not define nor rely on defining affordable housing but use the ratio as its measure to quantify its relation to other economic variables and responses to policy.

Affordability and policy

In the UK, the government policy is to increase the supply of housing in order to improve affordability in the greater South East. This appears to be a natural response to rising house prices and reports of housing shortages (Barker, 2004). With White and Allmendinger (2003) as well as Whitehead (2007) arguing that housing shortages are a result of strict planning policies, it appears that the government has a key role to play in resolving the housing crisis. As Gurran and Whitehead (2011) argue, new supply of affordable units is a function of planning regulations, development controls and fees. Since all of those factors can be affected by policy, it appears that the recipe for increasing housing affordability may be quite simple. However, despite policy design that supports provision of affordable housing and generous incentives for such developments (Morrison and Monk 2006) the problem remains unresolved. In fact, Crook et al. (2010) show that existing policies produce a supply of dwellings that is lower than expected but also that building new homes in the most critical areas has little effect on affordability.

More recent studies indicate that simply increasing supply may not be sufficient to reduce prices. Fingleton (2008) notes that both supply and demand factors need to be considered when trying to design policies that affect house prices. If the increase in the supply of housing is accompanied by expansion of employment there might be a feedback effect on demand for residential properties. This resonates with the argument presented by other researchers (Glaeser et al. 2006, Szumilo et al. 2017) who note a reciprocal relationship between city size, productivity and income. Gurran and Whitehead (2011) also argue that supply-focussed policies may be misguided and that demand also needs to be addressed. The key concept is that under certain conditions expansion of supply can increase demand and lead to higher prices (Nelson et al. 2002).

3. Measuring housing affordability

The previous section showed that an analysis using a simplistic definition of affordability is likely to yield misleading results due to the large variations in building stock, regional wealth and endowment with local amenities and production factors which are reflected in house prices. Therefore, a conceptual framework is required that takes these factors into account. An obvious starting point is the quintessential urban economics models of urban house price determinants, the Alonso-Muth-Mills model, which assumes that locations closer to an urban and/or major employment centre are more attractive due to greater accessibility and shorter commutes and will hence command higher land and house prices. Households maximise their utility by trading off the accessibility and other amenities of a given location with the cost of housing and transportation. The cost of housing is assumed to fall linearly as transport costs increase with distance to the centre which means that the sum of these two key costs is assumed to remain constant across space. However, households, particularly those with higher incomes, are able to gain higher utility by consuming more floorspace on larger parcels of land in more peripheral locations which may more than offset the additional cost of longer commutes and travel times. While the Alsonso-Muth-Mills model explains the general price distribution within a city, it fails to explain price differentials across cities. To this end, Rosen (1979) and Roback (1982) incorporate the role of wages and rents in household location choices. In the Rosen-Roback model, prices reflect wage levels and/or the aggregate value of amenities across cities. Roback’s empirical analysis infers the implicit willingness to pay for location amenities by comparing wages net of housing costs across cities and finds that workers accept lower real wages in areas with a high level of amenities. This finding was also confirmed for the UK housing market by Gibbons et al (2011 and 2014).

Fundamental determinants of house prices

Glaeser et al. (2006) demonstrate that new supply plays a crucial role in determining whether productivity increases will lead to urban expansion or just to more expensive homes and higher wages. The former is shown to occur in places with low regulation and low density while the latter is associated with cities marked by high density and strict planning regulations. Where housing supply is extremely inelastic, population size remains constant and wages increase to offset the accompanying rise in house prices following an increase in demand. However, these constraints can be partially circumvented by longer commutes from areas with more elastic supply and by pricing out and replacing existing low-skilled residents by highly-skilled, more productive incoming workers. This is not undisputed, however, as Ortalo-Magne and Rady (2008) demonstrate that established long-term homeowners typically remain in a neighbourhood even if they could afford a larger property elsewhere following sharp house price increases in their neighbourhood. Competition for available properties is then restricted to highly-skilled affluent newcomers. By contrast, pricing out may occur where households are mainly renters and not protected by strict regulations on rent increases.

Differences between short and long-run house price determinants are also expounded in the literature. For example, MacDonald and Taylor (1993) explore the long-run relationships between house prices in the UK and then work out potential ripple effects and short-term dynamics. More recently, Gallin (2006) investigated the long-run relationship between house prices and income and did not find a significant association. Generally, long-term house price determinants include demographic trends, household size, household income, taxation of home ownership as well as transportation cost and technology while short-term factors include unemployment, interest rates, access to mortgage debt and the financial performance of competing asset classes (Malpezzi 1999, Meen 2002, Weiner and Fuerst 2017).

Inelastic supply of housing has been shown theoretically and empirically to inflate house prices in the presence of rising demand. This may lead to house prices growing faster than wages, thereby eroding affordability. While this outcome is not desirable in terms from a policy and household purchasing power point of view, it could be argued that if increased demand for housing is correlated with growing demand for labour, the local economy still benefits from lower unemployment rates and higher wages. While the benefit of higher earnings would be offset partially or completely by the inflation of house prices, higher employment is expected to persist. This would also be true at a national level assuming that the size of the labour force is constant. In that case, if a growing economy wanted to sustain its development by increasing its total employment, it would have no choice but to hire and train previously unemployed workers (Aslund and Rooth 2007). However, at a regional level, the size of the labour force could evolve as the transport infrastructure changes. Given satisfactory transportation links, the labour force would not be constant despite the fact that local population in the centre of employment may remain unchanged and limited by an inelastic supply of housing (Haynes 1997). This shows that when analysing a particular housing market, its interaction with commutable areas also needs to be examined. Hence, the current study can be seen as an extension of the work presented by Glaeser et al. (2006) who assume that there is no cross area commuting and model house prices based on within-area supply and demand. However, the present analysis relaxes the assumption that demand is only driven by local employment by also taking moving and commuting across areas into account.

Modelling the interaction between housing and labour markets

Workers who purchase or rent homes in expensive locations would be those with the highest utility derived from doing so. For example, senior workers whose opportunity cost of commuting is high could be more likely to live close to their workplace (Bissell 2014, Eliasson, et al. 2003). In a competitive bidding process, prices would increase and houses would be more likely to be occupied by those who derive higher utility from living close to the centre. However, it is also important to consider that those who have the ability to pay more are likely to outbid those whose maximum price is constrained not by their utility but by their wage (Sa 2015). Consequently, house prices in any district are likely to be determined by wages offered to those who work there and the number of workers competing for housing in the location. While not everyone may prefer to live close to their workplace, those with higher wages can afford to pay higher prices in exchange for a less onerous commute. If income (*I*) in area *i* at time *t* is defined by the Hadamard (cell by cell) product of the *N* by 1 vector of mean employee mean wage rate $\bar{w}_t$ and number of employees working in each District E_t, hence $I_{it} = \bar{w}_{it} \circ E_{it}$, then its growth can be driven by changes in either of those values. However, they are likely to have different effects on the affordability ratio defined as $\frac{p_{it}}{\bar{w}_{it}}$ (where *p* is price). If residential demand (q_{it}) is driven primarily by changes in income $q_{it} = f(p_{it}, I_{it})$, then as income grows, house prices increase accordingly (Goodman 1988). However, the impact of this process on the affordability ratio depends on whether the higher income is driven by employment or wages. While both can impact prices through demand, only wages can induce a corresponding change in the affordability ratio. In this light, an expansion of housing supply can be seen as an increase the number of local workers. This will increase income and house prices unless it is accompanied by a reduction in average wage levels. Glaeser et al. (2006) present this process by introducing a wage model which assumes that agglomeration benefits have a positive effect while a negative reaction is caused by the increasing labour supply. We adopt a simpler approach in which we do not allow wages to be a function of the local labour force but assume that they are set exogenously for each district. This focuses our study on the housing demand created by the increase in employment levels and ignores the impact of additional density on wages. Omitting the density effect simplifies our analysis and assumes that the impact of new housing supply on demand is lower by ignoring one of the channels of its transmission. According to Fingleton (2008) doubling employment density in UK districts increases wages by 2.8%. This effect is unlikely to have a significant impact on our analysis as the highest changes in employment density in our simulation will not exceed 50% so changes in wages will be very small. Moreover, if this assumption has any effect on our estimates it would be a small downward bias in the impact of new supply on prices. In our set up, new housing supply increases income by allowing more workers (rather than higher wages). In turn, this is likely to lead to a higher housing demand. Ultimately, the impact of new supply on affordability will depend on income elasticity of demand and supply elasticities of both income and price.

While a similar process has been shown by Glaeser et al. (2006), their work has explicitly ignored any interactions between locations. If the demand for housing from residents of any district is allowed to depend on income earned by residents commuting to jobs located within commuting distance of that district, it becomes necessary to consider how this interaction may affect the impact of supply increases on prices. In other words, the jobs that determine local income are not local but distributed across commutable areas (Mulalic, et al. 2014). This means that the impact of increasing local supply in district *i* will be affected by demand generated by commutable jobs which we denote by I_{it}^{c}, which is income within commuting distance. We also include a spatial price dependence element $\left(W_N p\right)$ and two district-invariant variables in the demand function, B_t and F_t, which becomes $q_{it} = f(p_{it}, I_{it}^{c}, W_N p_{it}, B_t, F_t)$. This reflects the fact that demand for property q_{it} depends not only on local prices and income within commuting distance, but on prices in 'nearby' districts, where 'nearby' means within commuting range, and on the Bank of England interest rate B_t and the FTSE ALL SHARES index of share prices[3] F_t. In order to calculate the mean Bank rate for each year, we take the mean of the rates applying in each month of the year. Bank interest rate is proposed to capture the effect on demand of (closely related) mortgage interest rates. It also reflects returns on investments held as Bank deposits, as an alternative to property investment. The mean FTSE ALL SHARES index is similarly meant to capture competing investment opportunities. Its annual value is calculated as the average level of monthly closing values of the index as reported by Bloomberg.

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[3] Divided by 1000.

We assume that prices will be correlated contemporaneously across space. That means that prices will tend to be related in districts that are close together in space as well as in time. For example, two identical properties on either side of a street would undoubtedly see a convergence in price because of comparison effects. We can think of this as a displaced demand effect, whereby an initially more expensive property would displace demand to a closely comparable property thus lowering the price of one and raising the price of the other, until an equilibrium is reached. We envisage a similar process operating at the district level, where, having controlled for other factors affecting prices, including inter-district heterogeneity, there will be a tendency for prices to convergence in locations where price comparisons are being made. Critically however, we assume that those comparisons will be made based on commuting possibilities between zones as workers from each district affect the demand in its commutable areas.

Introducing this regional price interaction between commutable areas needs to be put in the context of the imperfections of both real estate and labour markets that determine it. Both markets are characterized by long search times, sticky prices and high transaction costs (Lambson et al. 2004). This results in changes occurring slowly and current prices being highly dependent on their historical values. One way to visualize this is as an imperfection in the market, so that the full effect of a change in price is not felt immediately. One might imagine that the full effect of rising prices will be moderated by institutional rigidities in the housing market, so that consumers already locked into the purchasing process will maintain their demand despite a price shock because of the costs of withdrawal due to commitments already entered into. Similarly, a delayed response to rising prices may be the outcome of imperfect knowledge of substitutes, for example there will be a cost of acquiring knowledge of, and access to, the rental market. We assume that the effect of a price adjustment is distributed over two years rather than being instantaneous. Including lagged prices in both supply and demand is consistent with the work of Meen (2005) or Holly et al. (2011) for the UK and with the approach of Iacoviello (2005) for the US. While this spatial dependency necessitates including a temporal lag factor (P_{it-1}) into the demand equation it presents an interesting problem in the light of the spatial correlation in house prices. If district-specific demand effects are distributed over two time periods, then their spatial effects should not be assumed to occur instantly but follow the same temporal process. As suggested by Doran and Fingleton (2017) it appears that a temporal lag of the spatial lag (WP_{it-1}) also needs to be included in the model to control for this process.

There are also potentially additional unmeasured effects, such as demand coming from non-wage earners, local taxes and amenities and the likely returns from investing in a neighbourhood[4]. These unmeasured effects, accounting for time-constant across-district heterogeneity together with additional transient effects, are represented in our model by random disturbances ω_{it}. Finally, for each of the Districts included in our analysis the proposed demand function can be formalized as:

$$q_{it} = f\left(p_{it}, p_{it-1}, I_{it}^c, W_N p_{it}, B_t, F_t, W_N p_{it-1}, \omega_{it}\right)$$

In which q_{it} is the demand for housing in District *i* (*i* = 1,…,*N*) at time *t*, I_{it}^c is income within commuting distance, p_{it} and p_{it-1} are prices and prices lagged by one year, $W_N p_{it}$ is the spatial lag of prices, B_t and F_t are the Bank rate and FTSE share index respectively, $W_N p_{it-1}$ is the spatial lag of the temporal lag of prices and ω_{it} represents other unmeasurable factors. To obtain I_{it}^c we commence with income by District, I_{it}, thus

$$I_{it} = \bar{w}_{it} \circ E_{it}$$

and this gives

$$I_{it}^c = \sum_{k=1}^{N} \tilde{C}_{ik} I_{kt}$$

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[4] Some Central London Boroughs consistently attract foreign investment. In 2012, estate agents Savills estimated the total value of housing stock in the London boroughs of Westminster and Kensington & Chelsea at £187bn, £11bn more than the value of the entire housing stock of Wales.

In which $\tilde{C}$ in an N by N matrix in which row i (i = 1,…,N) contains the proportions of commuters[5] travelling from District i to work in each of the N Districts.

We assume that price comparisons will involve Districts with similar locations with respect to the location of employment, and we measure this similarity by an N by N proximity matrix W_N . The effect of proximate prices is captured in the model by the vector $W_N p_t$, which is the matrix product of W_N and the price vector p_t thus

$$W_N p_{it} = \sum_{k=1}^{N} w_{ik} p_{kt}$$

Since large inter-District commuting flows are a good indicator of close proximity, the matrix W_N is taken to be the same as the weighting matrix used to give I_t^c , except that the leading diagonal cells are set to zero prior to standardisation[6]. Accordingly, cell i of vector $W_N p_t$ is a weighted average of Districts in the vicinity of i, with weights determined by proximity as given by inter-District commuting frequencies. Moreover because of market imperfections there is also an effect of proximate prices in the previous period, hence we include $W_N p_{t-1}$ in the specification.

We assume a linear demand function, with negative coefficients on price, except on the spatial lags of price where the displaced demand would tend to a negative relationship. However, in our reduced form, this is not identified so we do not explicitly test this hypothesis. We also anticipate that a higher bank rate with correspondingly higher mortgage rates and higher returns from savings will be associated with lower demand, and similarly a higher FTSE index indicates lower demand for housing with investment attracted to higher returns on investing in stocks and shares than property.

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[5] Commuting flow data from the UK 2001 Census. A sample of the full Table is given in the appendix.
[6] The frequency in each row divided by the row total.

$$q_{it} = a_1 I_{it}^c - a_2 p_{it} - a_3 p_{it-1} + a_4 W_N p_{it} - a_5 B_t - a_6 F_t + a_7 W_N p_{it-1} + \omega_{it} \qquad (1)$$

On the supply side, the variables are the same, except that we substitute the stock of dwellings (S_{it}) for income within commuting distance, and there are different assumptions about the signs on the coefficients. This is apparent from equation (2),

$$\begin{aligned} q_{it} &= f(p_{it}, p_{it-1}, S_{it}, W_N p_{it}, B_t, F_t, W_N p_{it-1}, \varsigma_{it}) \\ q_{it} &= b_1 p_{it} + b_2 p_{it-1} + b_3 S_{it} - b_4 W_N p_{it} - b_5 F_t - b_6 F_t - b_7 W_N p_{it-1} + \varsigma_{it} \end{aligned} \qquad (2)$$

Thus, the quantity supplied increases with price and lagged price, with an assumption that development and selling will be stimulated by rising prices. The presence of the lagged prices is again a reflection of presumed market imperfection, with a positive price shock taking time to create a supply response, due to institutional factors and the time and finance required to respond to the price signal. Supply is also assumed to be a positive function of the stock of dwellings in each District, with Districts with a large dwelling stock (the larger towns) naturally being associated with a large supply of properties on the market irrespective of prices. Also we assume that supply will be lower if money is held as savings and investments and mortgages to finance development are expensive, hence the negative signs on B_t and F_t. As with the demand function, we also include spatial lags $W_N p_t$ and $W_N p_{t-1}$ to reflect a similar process of proximate price comparison in this case involving developers and sellers. For example, if prices are higher on one side of a street of identical properties, the residents and builders are more likely to place properties on the market, thus increasing supply and reducing selling prices. On the other side of the street, reluctance to place properties on the market until prices rise will inhibit supply and cause prices to rise, until eventually we reach an equilibrium. Likewise, at the District level, high prices in nearby Districts will, ceteris paribus, tend to be negatively related to the quantity supplied in District *i* on an assumption that high prices 'nearby' encourage developers and builders who would otherwise increase the supply in District i to prefer to build or renovate in nearby Districts, and householders in *i* will be reluctant to put their properties on the market until prices rise to the level in surrounding Districts. We refer to this as a displaced supply effect. This rationale is reflected in the negative coefficients on the spatial lags $W_N p_t$ and $W_N p_{t-1}$ in the supply function. For simplicity, W_N is the same as in the demand equation. The disturbances ς_t again capture unmeasured effects such as inter-District heterogeneity.

4. Data and preliminary analysis

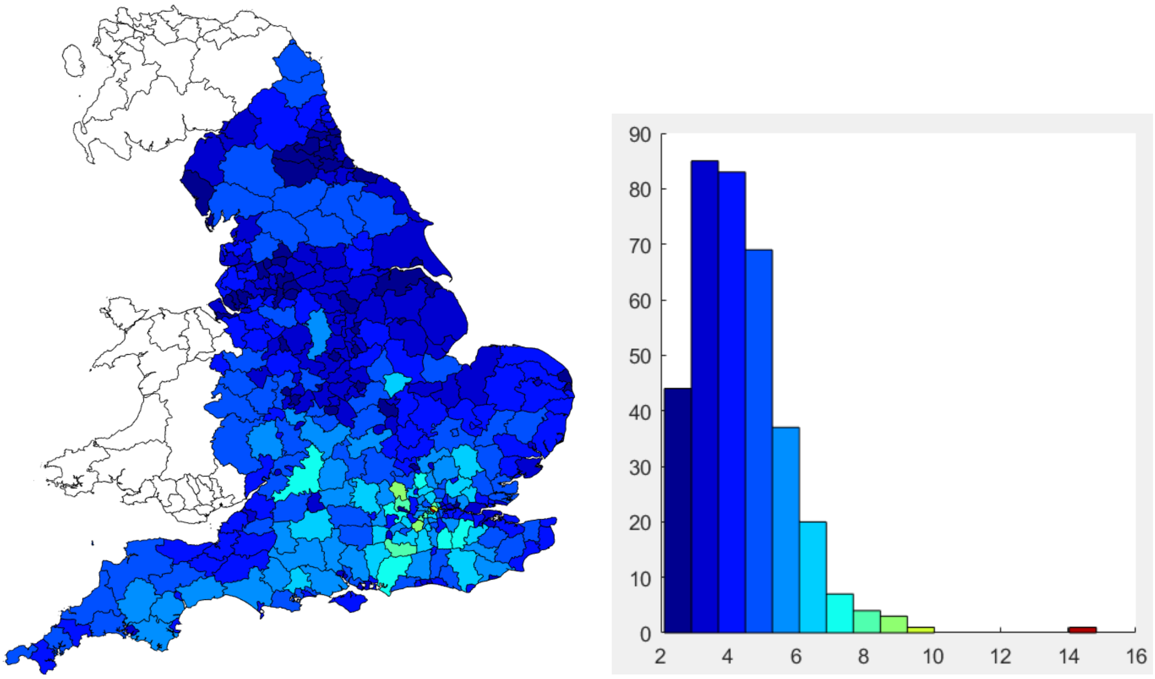
The essential departure in this paper, compared with the purely cross-sectional approach in Fingleton (2008), is an emphasis on dynamics. To set the scene, let us look at wage and price data for the years 1998 and 2012, which is the period over which we estimate our model. Figure 1 gives a snapshots of the price to average wage ratio at the beginning and end of our estimation period. The data are taken from the UK's Office of National Statistics and the Land Registry, and are means in each Unitary Authority and Local Authority District (hereafter referred to as Districts) taken across all types of property selling prices and all employees at places of work. Districts are used because their internal housing markets are relatively uniform and are divided into four different types (London Boroughs, Non-metropolitan Districts, Metropolitan districts and Unitary Authorities) based on their geography and population. Since each is governed by its own local authority, planning and housing policies are similar within those areas but differ across them. These are also the smallest geographical units for which data on wages is available. Naturally, because the areas are quite small (see table 1) there is a large amount of cross-commuting, especially in the Greater London area. Controlling for this effect is the cornerstone of this paper and commuting data from the 2001 census is used to model the relationship between places of work and residence. This allows us to reflect in empirical analysis the fact that labour markets span multiple districts.

Table 1. Summary statistics and differences between districts over time.

2008	**House prices**		**Affordability**		**Wages**		**Population**		**Density**	
LA type	Average	*StdDev*	Average	*StdDev*	Average	*StdDev*	Average	*StdDev*	Average	*StdDev*
London Borough	296,881	7,733	9.12	1.72	593.1	80.4	243,906	51,485	66.86	33.76
Metropolitan District	130,330	18,923	5.49	0.51	438.4	30.2	312,408	174,472	20.06	9.75
Non metro	193,004	52,828	7.30	1.48	486.9	68.5	104,320	28,994	7.16	8.62
Unitary Authority	164,932	48,724	6.46	1.34	467.8	66.9	187,262	68,241	18.47	15.52
2012										
London Borough	323,533	133,285	9.40	2.71	623.3	70.6	259,406	56,594	71.03	35.83
Metropolitan District	123,090	20,862	4.88	0.53	465.7	35.3	320,878	182,937	20.59	10.25
Non metro	190,390	58,938	6.77	1.50	514.8	71.1	106,957	30,230	7.38	8.97
Unitary Authority	160,985	51,646	5.99	1.35	491.1	66.8	193,394	71,712	19.18	16.30

From Figure 1, we see that the price to wage ratio had increased quite dramatically over the period, indicating falling affordability[7].

Figure 1: House price to annual wage ratio in 1998 (top) and 2012 (bottom), England



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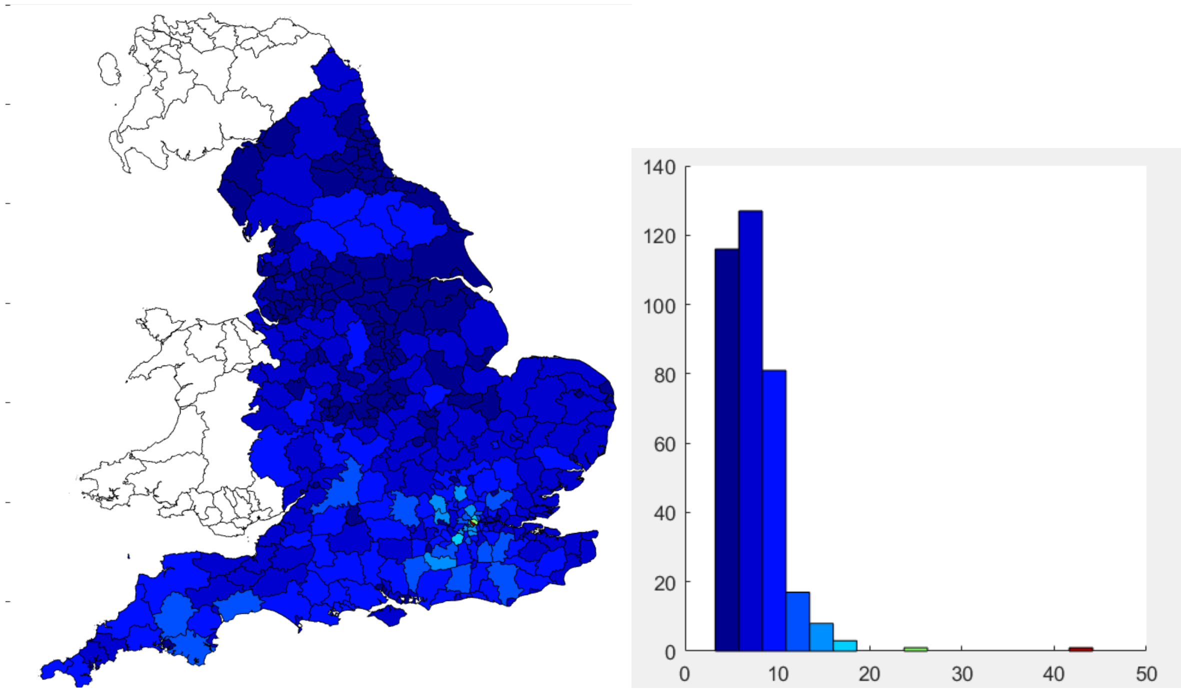
[7] The outlier is the London Borough of Kensington and Chelsea.



Key: Vertical scale: number of Districts; Horizontal scale: price to annual wage ratio. Shades on the map and the histogram correspond to the same price to annual wage ratio. The histogram indicates the affordability ratio corresponding to a specific colour and presents the frequency of this ratio while the map shows the spatial distribution.

5. Model specification

This section describes the econometric methodologies used to estimate the reduced form equation and simulate its results in respective subsections.

It is easy to show that having normalised the supply function with respect to p_{it} , i.e. rearranging Equation 1 with price on the left hand side, and then substituting for q_{it} using the demand function (equation 2), the reduced form is

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + \beta_1 I_{it}^{c} + \beta_2 S_{it} + \beta_3 B_t + \beta_4 F_t + \theta \sum_{k=1}^{N} w_{ik} p_{kt-1} + \varepsilon_{it} \qquad i = 1,\ldots,N; t = 2,\ldots,T \tag{3}$$

We also include random effects μ_i taking account of inter-District heterogeneity, and transient effects v_{it} picking up spatially and temporally varying shocks, and assume that the disturbances comprise an autoregressive spatial dependence process with the same weights matrix as the spatial lags in (3), but with parameter ρ_2 .

$$
\begin{aligned}
&\varepsilon_{it} = \rho_2 \sum_{k=1}^{N} m_{ik}\varepsilon_{kt} + u_{it} \\
&\varepsilon_t = (I_N - \rho_2 W_N)^{-1} u_t = H_N^{-1} u_t \\
&u_{it} = \mu_i + \nu_{it} \\
&M_N = W_N \text{ an } N \text{ x } N \text{ matrix of known spatial weights} \qquad (4) \\
&I_N \text{ is an } N \text{ x } N \text{ identity matrix} \\
&\mu_i \sim iid(0, \sigma_\mu^2) \text{ the individual-specific time-invariant effect} \\
&\nu_{it} \sim iid(0, \sigma_\nu^2) \text{ the remainder effect} \\
&\operatorname{cov}(\mu_i, \nu_{it}) = 0
\end{aligned}
$$

Baltagi et. al. (2014) develop an estimator, with the acronym GMM-SL-SAR-RE[8], for an equivalent dynamic spatial panel model with autoregressive spatial disturbances but with θ restricted to zero, which is based on the work of Arellano and Bond (1991), and Mutl (2006), and on the spatial method of moments (GM) estimator proposed by Kapoor, Kelejian and Prucha (2007). Baltagi et. al. (2018) introduce an estimator based on this approach but with θ not restricted to zero, which differs from our estimator in that it assumes a spatial moving average error process for the disturbances. This is the basis of the estimator employed in this paper. We omit much technical detail but the basic idea is to include both non-spatial and spatial instruments in the estimator to obtain consistent estimates of the parameters. Monte Carlo simulations carried out by Baltagi et. al. (2014, 2018) show that for a data generating process with these characteristics, GMM-SL-SAR-RE is superior to OLS, which ignores the endogeneity of the spatial and temporal lags, the existence of individual effects μ_i and the spatial dependence in the disturbances. Likewise, it is preferable to the Within or Fixed Effects estimator, which does take care of μ_i but which also does not deal with the endogeneity of the lags or the spatial dependence in the disturbances. Also the original Arellano and Bond (1991) GMM estimator ignores the spatial process in the disturbances, while the estimator of Mutl (2006) which does not include the spatial lag, so these too perform less well than GMM-SL-SAR-RE.

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[8] GMM estimation of a model with a spatial lag and spatially autoregressive random effects.

To summarise, following Arellano and Bond (1991) and Baltagi et al (2014, 2018), we eliminate the individual effects μ_i , which are correlated with the spatial lag and temporal lags of the dependent variable, by first differencing the model. Next, again following this literature, moments conditions are created on the basis of an assumption of no correlation between first differenced disturbances and time lagged levels of variables. As explained in Bond (2002), the extent of lagging depends on whether variables are considered exogenous, pre-determined or endogenous. In this particular application, the variables I_t^c and S_t are assumed to be pre-determined, which means they are contemporaneously uncorrelated with the v_{it}, but may be correlated with the v_{it-1} and earlier shocks. We therefore assume that prices may feedback and affect income and supply, but this effect is not instantaneous. Following Bond (2002), these predetermined variables are lagged by one period in the construction of moments equations so as to eliminate correlation between the instruments at time $t-1$ and earlier and Δv_{it}. Likewise, the spatial lags of these variables are also lagged by one period to give an enhanced set of moments equations. Using these instruments in a spatial GM estimator we obtain consistent estimates of $\gamma,\rho_1,\beta_1,\beta_2,\beta_3,\beta_4,\theta$. The first differenced residuals provided allow estimation, using nonlinear least squares to solve the sample moments, of $\rho_2,\sigma_v^2,\sigma_\mu^2$ based on Kapoor, Kelejian and Prucha (2007). Finally, again following Arellano and Bond (1991) and Baltagi et al (2014, 2018), we obtain final estimates of $\gamma,\rho_1,\beta_1,\beta_2,\beta_3,\beta_4,\theta$ via a two-step spatial GM estimator. We omit technical detail of the robustness of these estimates which is available in Baltagi et al (2014, 2018).

We estimate the model using data for the period 1998 to 2011, thus omitting the most recent observations for 2015, which are retained to enable one-step ahead predictions. Table 2 gives the resulting parameter estimates, standard errors and t ratios, indicting highly significant temporal and spatial lags, a very strong positive relationship between price and income within commuting distance, and a strong negative relationship between the stock of dwellings and price. There is also positive spatial dependence among the disturbances, but the individual heterogeneity (as measured by the estimated σ_μ^2) is comparatively large compared to the variance of the transient effects $(\hat{\sigma}_\nu^2)$. According to Elhorst (2001, p. 131), Parent and LeSage (2011, p. 478, 2012, p. 731) and Debarsy, Ertur and LeSage (2012, p. 162), the dynamic stability and stationarity of the model requires that

$$\begin{aligned} &\gamma+(\rho_1+\theta)e_{\max}<1 \quad \text{if} \quad \rho_1+\theta\geq 0 \\ &\gamma+(\rho_1+\theta)e_{\min}<1 \quad \text{if} \quad \rho_1+\theta<0 \\ &\gamma-(\rho_1-\theta)e_{\max}>-1 \text{ if } \rho_1-\theta\geq 0 \\ &\gamma-(\rho_1-\theta)e_{\min}>-1 \text{ if } \rho_1-\theta<0 \end{aligned} \tag{5}$$

In which *e* is a vector of eigenvalues of W_N. Given $e_{\max}=1$ and $e_{\min}=0.001$ and using the parameter estimates in Table 2, we conclude that the model is stationary.

Table 2: GMM-SL-SAR-RE estimates of the dynamic spatial panel model

parameter	estimate	St. error	t ratio
γ	0.9518	0.001283	742.1
ρ_1	0.583	0.004454	130.9
β_1	270.3	6.663	40.57
β_2	-0.9701	0.02689	-36.08
β_3	-1.687	0.02743	-61.5
β_4	-4.016	0.06409	-62.67
θ	-0.585	0.004215	-138.8
ρ_2	0.4555		
σ_μ^2	3.6806		
σ_ν^2	2.1518		
Notes: Standard errors for estimates of ρ_2,σ_ν^2 and σ_μ^2 cannot be estimated using standard techniques and therefore are not reported in this table. The influence of ρ_2 on the model can however, be inferred from the results of one-step ahead predictions reported below.			

The on-step ahead predictions for 2012 were obtained following Chamberlain (1984), Sevestre and Trognon (1996), and Baltagi et al (2014), who proposed a linear predictor of (3) under the assumption that $\theta=0$. But this also depends on a process that generates initial values which could be impracticable. In this section, we give an alternative predictor for the case where $\theta\neq 0$ and which does not depend on the generation of unobserved initial values p_0. Following Baltagi et al (2018), but in the context of spatial autoregressive errors, as a first step, we obtain estimates of the individual effects μ_i from the residuals averaged over time. Thus, we commence with the equation (3) specification written thus

$$\begin{aligned} p_t &= \rho_1 W_N p_t + \beta_1 I_t^c + \beta_2 S_t + \beta_3 B_t + \beta_4 F_t + C_N p_{t-1} + \varepsilon_t \\ C_N &= \left(\gamma I_N + \theta W_N\right) \end{aligned} \tag{6}$$

in which $\rho_1, \gamma, \beta_1, \beta_2, \beta_3, \beta_4$ and θ are scalar parameters and I_N is an N by N identity matrix. And given the SAR error process based on scalar parameter ρ_2 and thus $H_N = \left(I_N - \rho_2 W_N\right)$, this leads to

$$\varepsilon_t = H_N^{-1} u_t = p_t - \rho_1 W_N p_t - C_N p_{t-1} - \beta_1 I_t^c - \beta_2 S_t - \beta_3 B_t - \beta_4 F_t \tag{7}$$

So that

$$\begin{aligned} u_t &= \mu + v_t = H_N \left(p_t - \rho_1 W_N p_t - C_N p_{t-1} - \beta_1 I_t^c - \beta_2 S_t - \beta_3 B_t - \beta_4 F \right) \\ \mu &= H_N \left(p_t - \rho_1 W_N p_t - C_N p_{t-1} - \beta_1 I_t^c - \beta_2 S_t - \beta_3 B_t - \beta_4 F \right) - v_t \end{aligned} \tag{8}$$

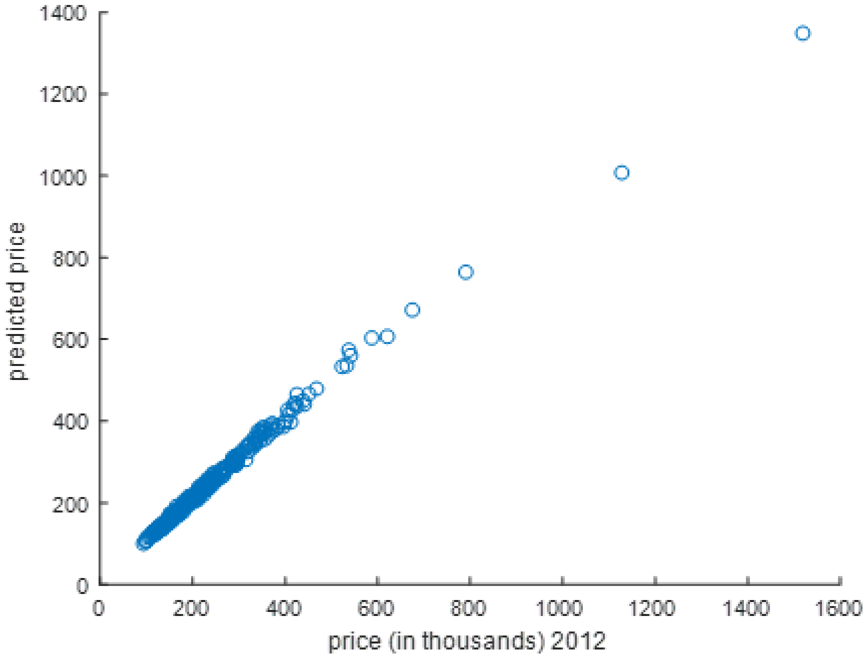
We obtain $\hat{\mu}$ by using the *N* x 1 observed price series p_t together with I_t^c, S_t, B_t, F_t and $\hat{\rho}_1, \hat{\gamma}, \hat{\theta}, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\rho}_2$ as given in Table 2, and drawing an *N* x 1 vector v_t from the $N(0, \hat{\sigma}_v^2)$ distribution to give $\hat{\mu}$ for each of $t = 2, \ldots T$. We take the time mean of these $T-1$ different estimates, over the years 1998 to 2011, to give an estimate of the time-constant *N* x 1 vector μ. We denote this estimate by $\bar{\mu}$.

Given $\bar{\mu}$, we obtain a price prediction for 2012 using the estimates $\hat{\rho}_1, \hat{\gamma}, \hat{\theta}, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\rho}_2$ obtained from data for the period up to 2011 combined with the observations on the explanatory variables for $\tau = 2012$, thus ensuring that the parameter estimates are independent of the 2012 data and providing a valid method for testing the predictive ability of the model. Therefore, predictions are obtain using the prediction equation

$$\begin{aligned}
\hat{p}_\tau &= \hat{B}_N^{-1}\left[\hat{C}_N p_{\tau-1} + \hat{\beta}_1 I_\tau^c + \hat{\beta}_2 S_\tau + \hat{\beta}_3 B_\tau + \hat{\beta}_4 F_\tau + \hat{H}_N^{-1}\bar{\mu}\right] \\
\hat{B}_N^{-1} &= (I_N - \hat{\rho}_1 W_N)^{-1} \\
\hat{C}_N &= \left(\hat{\gamma} I_N + \hat{\theta} W_N\right) \\
\hat{H}_N^{-1} &= (I_N - \hat{\rho}_2 W_N)^{-1}
\end{aligned} \tag{9}$$

The predicted and actual prices for 2012 for each of $N = 353$ districts are given in Figure 2, and this indicates that the model works quite well for most districts.

Figure 2: One-step ahead predictions



A measure of the relative predictive ability of the model versus various sub-models in which various parameters are restricted to zero, is given by the root mean square error (RMSE), where

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(\hat{p}_\tau - p_\tau\right)^2}{N}} \tag{10}$$

Table 3: RMSEs for one-step ahead predictions given by prediction equation (9) and sub-models

Full model	$\rho_1 = 0$	$\gamma = 0$	$\theta = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\rho_2 = 0$
17.4213	168.8065	641.2378	445.7474	58.7971	201.8032	93.0538
	$\beta_3 = 0$	$\beta_4 = 0$				
	203.7190	230.2032				

Table 3 shows the loss of fit relative to the predictions given by the full model that occurs when the various model parameters are constrained to zero. An RMSE value similar to that for the full model would indicate that a given restriction was acceptable and make no difference to the predictive performance of the model. However, we find that the RMSEs reflect what is shown by the t ratios in Table 2. While the estimator does not provide a t ratio for ρ_2, interestingly, assuming no spatial dependence in the errors ($\rho_2 = 0$) produces a larger RMSE than nullifying the effect of demand variation.

Simulation Methodology

The motivation for our simulation is to try to quantify what effect an localised autonomous increase in the supply of dwellings would have on local and regional house prices and affordability. The approach adopted is to use the parameter estimates given in Table 2 to generate 'what if' scenarios, in other words house prices under an assumption that the number of dwellings was much larger than actually observed in specific locations[9]**.** The very small standard errors of the estimated model mean that within the range of variation this allows, the variation in simulation outcome is likely to be small.

$$\hat{p}_\tau = \hat{B}_N^{-1}\left[\hat{C}_N p_{\tau-1} + \hat{\beta}_1(I_\tau^c + \Delta I_\tau^c) + \hat{\beta}_2(S_\tau + \Delta S_\tau) + \hat{\beta}_3 B_\tau + \hat{\beta}_4 F_\tau + \hat{H}_N^{-1}\bar{\mu}\right] \tag{11}$$

---

[9] The specific locations are the 32 Boroughs plus the City of London, collectively known as the 33 Boroughs of Greater London. We explore the consequences for residential property prices and affordability of increasing the aggregate number of dwellings in these districts.

To obtain the counterfactual price for the year $\tau =$ 2012 (for which we have data), counterfactual values for demand and/or supply are utilized, as denoted by $I_{\tau}^{c} + \Delta I_{\tau}^{c}$ and $S_{\tau} + \Delta S_{\tau}$. Also the 2012 mean Bank rate and FTSE index are used for B_{τ} and F_{τ}. Initially, the level of housing supply in each London Borough was incremented by 5%, and then by 15%. We also explore the ramifications for prices and affordability on the basis of 1.6 million more homes across Greater London, which on our estimation is an increment of approximately 48% in the stock of homes. Counterfactual price series were obtained on the assumption that there was no concomitant increase in the demand for housing, so that $\Delta I_{\tau}^{c} = 0$ across all districts and $\Delta S_{\tau} = 0$ outside of Greater London. Elsewhere, within Greater London, $\Delta S_{i\tau} = 0.05 S_{i\tau}$ and alternatively $\Delta S_{i\tau} = 0.15 S_{i\tau}$.

In addition, we make the assumption that a higher level of supply would entail higher-level demand as more workers occupy the additional accommodation. In our estimation of the counterfactual level of demand in 2012, we simply utilize wages at their 2012 levels. To obtain the change in income within commuting distance $\Delta I_{i\tau}^{c}$ we use essentially the same method used for I_{it}^{c} as described earlier. Thus, we need to estimate the increase in income by District, $\Delta I_{i\tau}$, which is approximated by the Hadamard product of the *N* by 1 vector of mean employee wage rate $\overline{w}_{\tau}$ and the increase in the number of employees working in each District ΔE_{τ}. To obtain the increase in employment level ΔE_{τ}, we calculate the ratio of the total number of workers in England to the total number of dwellings, thus eliminating the effects of commuting. The employment increase ΔE_{τ} is equal to the dwellings increase ΔS_{τ} multiplied by this ratio, which is equal to zero for all but the London Boroughs. Thus

$$\Delta I_{i\tau} = \overline{w}_{i\tau} \circ \Delta E_{i\tau} \tag{12}$$

and this gives

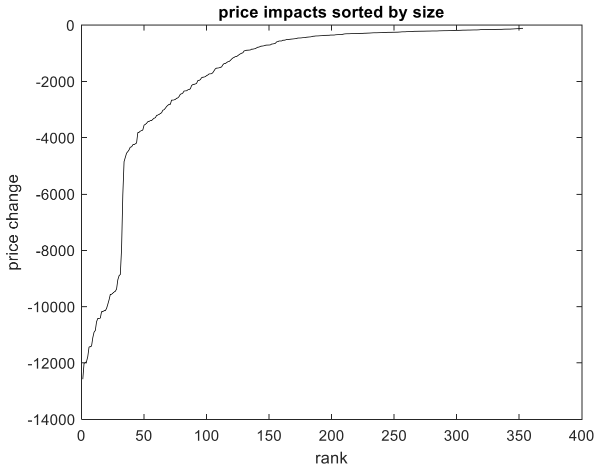
$$\Delta I_{i\tau}^{c} = \sum_{k=1}^{N} \tilde{C}_{ik} \Delta I_{k\tau} \tag{13}$$

6. Results

Figure 3 shows the impact, as given by equation (8), of a hypothetical step increment of 5% in the number of dwellings in each of London Boroughs (plus the City of London) on its 2012 level. To interpret Figure 3, Districts across the whole of England have been sorted according the strength of the impact on price.

Figure 3. Impact of 5% increase in supply in London house prices

Districts are ranked according the strength of the impact



This shows that within Greater London the extra supply of housing produces a fall in price of between about £4,000 to £12,000. Many other areas of England see prices fall by less than £4,000 but this is in response to an increase in supply confined to Greater London. This is also illustrated by the Figure 4a histogram which gives the distribution of price impacts across all English districts. The Figure 4b map focuses on price changes in the South East of England, centred on London, which sees the greatest impact. The darkest shading highlights the London Boroughs, but spillover effects are also felt outside the area actually receiving the supply-side stimulus.

The simulations described in Figure 4 assume that an increase in supply occurs without any concomitant increase in demand. However, demand may change due to the increase in the number of dwellings generating an increase in the workforce and therefore income. Figure 5 shows the increase in price due to the induced increase in demand. Prices would rise by about £2,500 in Inner London. Figure 6 gives the net outcome of the negative supply effect plus the positive demand effect, showing that prices fall by about £4,000 to £10,000 in the London Boroughs, with spillover causing price reductions outside London. Of the 353 English Districts, more than 200 do not see any price effect as a result of the increased supply of dwellings in London. Tables 4 and 5 give quantitative details. While prices reductions would be the outcome of a 5% increase in supply, the small scale of the effect would make hardly any difference to affordability.

Table 4: Actual prices and affordability in 2012

	Price (£)		Affordability	
	mean	median	mean	median
Greater London	438,960	379,610	11.70	9.45
England	230,560	208,170	7.53	7.00

Table 5: The effects on prices and affordability in 2012 of a hypothetical 5% increase in supply

		Counterfactual price		Counterfactual Affordability	
Both supply and demand effects		mean	median	mean	median
	Greater London	431,329	372,004	11.49	9.23
	England	229,272	206,688	7.50	6.89
		Counterfactual price		Counterfactual Affordability	
Supply effects only		mean	median	mean	median
	Greater London	428,745	369,197	11.42	9.16
	England	228,711	205,886	7.48	6.88
Notes: With supply effects only, counterfactual price series were obtained on the assumption that there was no concomitant increase in the demand for housing, so that $\Delta I_{\tau}^{c} = 0$ across all districts and $\Delta S_{\tau} = 0$ outside of Greater London. Elsewhere, within Greater London, $\Delta S_{i\tau} = 0.05 S_{i\tau}$					

Figure 4: Effect of a 5% London supply

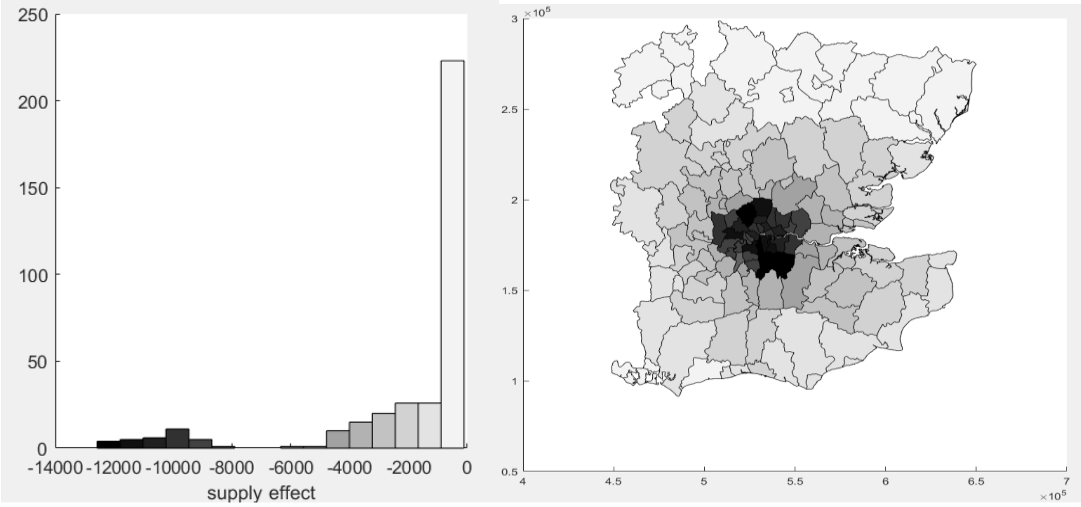


Figure 4a: England

Figure 4b: South East England

Key: Vertical scale: number of Districts; Horizontal scale: price to annual wage ratio. Shades on the map and the histogram correspond to the same price change.

Figure 5: Effect of demand increase due to a 5% London supply increase

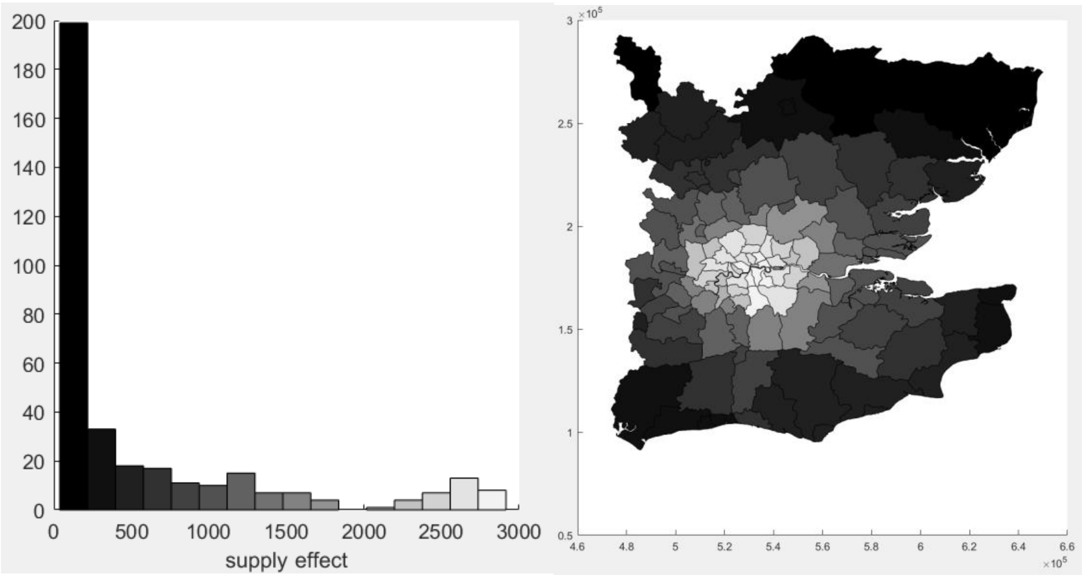


Figure 5a: England

Figure 5b: South East England

Key: Vertical scale: number of Districts; Horizontal scale: price to annual wage ratio. Shades on the map and the histogram correspond to the same price change.

Figure 6: Net effect of 5% increased supply and increased demand

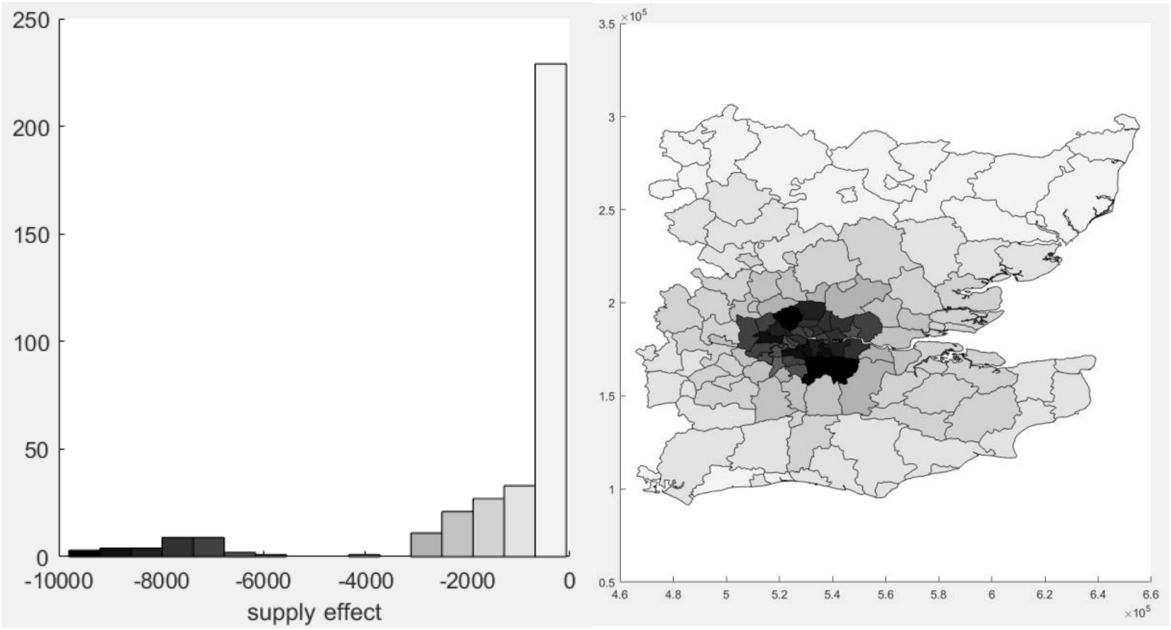


Figure 6a: England

Figure 6b: South East England

Key: Vertical scale: number of Districts; Horizontal scale: price to annual wage ratio. Shades on the map and the histogram correspond to the same price change.

In order to obtain a greater impact, we increase the existing supply of dwellings by 15%. The resulting Figures are similar to Figures 4, 5 and 6, so to save space we omit these. The greater increase in supply would cause prices to fall by approximately £30,000 in the London Boroughs, but with the spillover effect causing price reduction of elsewhere in the South-East of England and beyond. Again, assuming that increased dwellings has a concomitant effect on the number of workers and hence demand, prices would increase by about £8,000 in the Inner London Boroughs, with the net effect being a price fall of about £22,000 in the London Boroughs with smaller reductions outside Greater London. The summary of effects in Table 6 indicates that a 15% increase in supply in Greater London does make housing more affordable but not by a large amount, and it fails to eliminate the affordability gap between London and the rest of England. Figure 7 shows the resulting distribution of affordability[10] assuming both demand and supply effects. A significant aspect of this is the relatively more affordable housing in the Thames estuary, with price to wage ratios of approximately 5. In contrast, in Kensington and Chelsea has a ratio in excess of 40, reflecting the special status of this area as a recipient on inward property investment from overseas.

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[10] Affordability here is defined as simulated price, which is 2012 price plus net impact, divided by the assumed annual wage.

Table 6: The effects on prices and affordability in 2012 of a hypothetical 15% increase in supply

		Counterfactual price		Counterfactual Affordability	
Both supply and demand effects		mean	median	mean	median
	Greater London	416,061	356,791	11.07	8.80
	England	226,694	203,724	7.42	6.87
		Counterfactual price		Counterfactual Affordability	
Supply effects only		mean	median	mean	median
	Greater London	408,307	348,371	10.85	8.60
	England	225,012	202,706	7.37	6.81

Notes: With supply effects only, counterfactual price series were obtained on the assumption that there was no concomitant increase in the demand for housing, so that $\Delta I_{\tau}^{c} = 0$ across all districts and $\Delta S_{\tau} = 0$ outside of Greater London. Elsewhere, within Greater London, $\Delta S_{i\tau} = 0.15 S_{i\tau}$

Figure 7 : Affordability with 15% increased supply

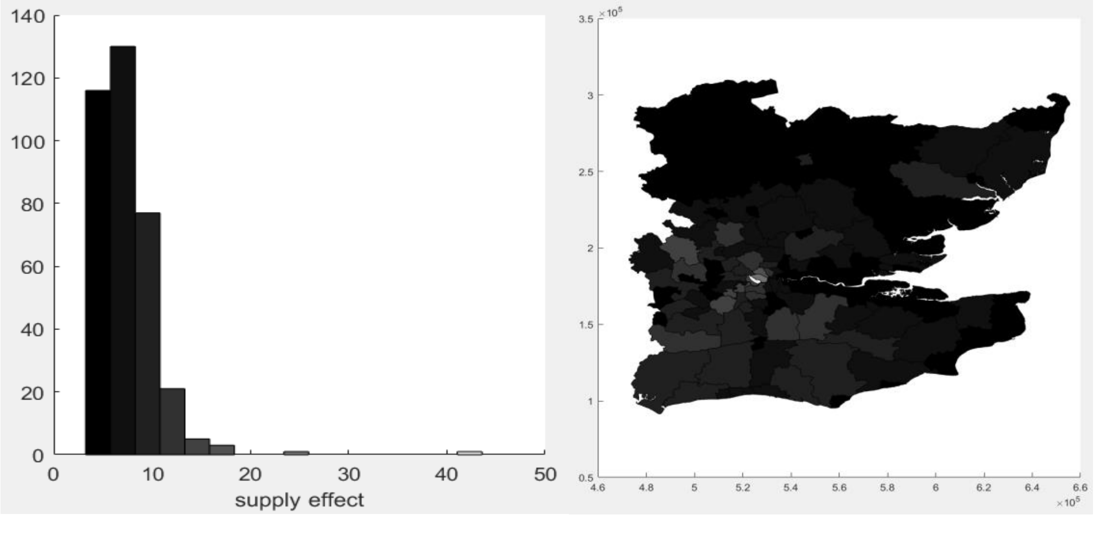

Figure 7a: England **Figure 7b: South East England**

Key: Vertical scale: number of Districts; Horizontal scale: price to annual wage ratio. Shades on the map and the histogram correspond to the same affordability ratios.

Table 7: The effects on prices and affordability in 2012 of a hypothetical 1.6M increase in supply

		Counterfactual price		Counterfactual Affordability	
Both supply and demand effects		mean	median	mean	median
	Greater London	383,058	345,647	10.09	8.36
	England	221,380	198,906	7.26	6.73
		Counterfactual price		Counterfactual Affordability	
Supply effects only		mean	median	mean	median
	Greater London	370,274	337,708	9.73	8.25
	England	218,238	195,157	7.16	6.67
Notes: With supply effects only, counterfactual price series were obtained on the assumption that there was no concomitant increase in the demand for housing, so that $\Delta I_\tau^c = 0$ across all districts and $\Delta S_\tau = 0$ outside of Greater London. Elsewhere, within Greater London we are allocating the 1.6M new housing units to London Boroughs on the basis of their share of green-belt land.					

Our final simulation is summarised by Table 7. This is based on the suggestion by Cheshire (2014) that 'building on greenbelt land would only have to be very modest to provide more than enough land for housing for generations to come: there is enough greenbelt land just within the confines of Greater London – 32,500 hectares – to build 1.6 million houses at average densities'. We put this to the test by estimating what the effect of an extra 1.6 million houses would be, in this case allocating the housing to London Boroughs on the basis of their share of green-belt land. This does have a major impact on affordability, reducing it to a mean of 9.73 and a median value of 8.25. Mean prices would fall by about £70,000. There is a marginal impact when we factor in the effect of increased demand is to raise mean affordability to 10.09 and the median rises to 8.36. These are both significantly below the 2012 mean and median values. Prices in this scenario are on average about £55,000 below what they otherwise would be. It might be supposed that the extra housing would be occupied by many commuters who currently travel in from outside Greater London, but for simplicity we have not adjusted the levels of housing demand downwards in out-of-London districts to allow for a potential exodus of former residents. If this was a large effect, then the lower prices out-of-London would to an extent spillover into Greater London itself and could have a further dampening effect on the level of prices and make housing more affordable. Likewise, if the new supply was largely filled by a 'churning' of Greater London residents, with Londoners moving out to former green-belt areas and releasing accommodation elsewhere in the capital, then extra demand in the green-belt could be to some extent compensated by the spillover effects of reduced demand elsewhere in London. In reality, new housing could be filled by a mix of current London residents, former commuters, and by migrants from outside the commuting belt or from overseas. The scale of these effects on demand is difficult to assess, but our estimation is that at best, with zero impact from additional demand, mean affordability would be 9.73, so even with this exceptionally large increase in the provision of housing services in Greater London, affordability is still worse than in England as a whole.

7. Conclusions

Housing affordability has been a key political and economic concern in the UK for a number of years. A lack of new housing supply in highly-priced areas is generally mentioned as the main cause of affordability problems. However, this study shows that simply increasing the stock of housing may not be sufficient for reducing prices as the corresponding demand also needs to be considered. Unlike Glaeser et al. (2006) we show that even if wages remain unchanged, new supply can have a much smaller effect on affordability than anticipated. This is mainly due to changes to the size of the local labour force, a factor that has been largely ignored in local and regional housing market forecasts.

Policies that reduce prices effectively are difficult to identify. In fact, even new supply does not appear to be a good way of reducing house prices as the corresponding demand also needs to be considered. Simulation results presented in this study show that improvements in the affordability ratio resulting from new supply are likely to be relatively modest. The key implication for policymakers is that they should carefully consider the interaction between supply and demand when designing and implementing new housing policies.

It is also important to note the effect of commuting patterns on housing markets. In this study, it is assumed that commuting costs will remain as in the Census year 2001. However, they have risen inexorably, up 18% over the last 3 years. With growing transport costs, it will become increasingly difficult to find substitutes for housing in a particular location. This is likely to increase house prices and reduce affordability. In turn, this would make long-distance commuting more attractive. If so, rising commuting costs are unlikely to reduce demand for it. Instead, the cost of the substitute (housing close to a workplace) is likely to grow accordingly. This shows that increasing commuting costs are likely to lead to lower housing affordability but not a reduced number of commuters. This has interesting implications for urban sustainability as it suggests that the best way to reduce commuting trips is to improve housing affordability. At the same time, it indicates that reducing transportation costs could help reduce house prices. More research is needed to confirm this logic but it appears that commuting patterns are closely linked to housing affordability.

Overall, our empirical prediction shows that increasing housing supply appears to have only a weak impact on affordability levels once the spatial dynamic effects of a supply shock are taken into account. Future work might seek to explore this prediction with more extensive empirical data.

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9. Appendix

Sample of the N by N (N=353) commuting matrix constructed using 2001 census - UK travel flows at local authority levels.

Table A1. A sample of the matrix of travel flows between districts.

	Luton	Mid Bedfordshire	Bedford	South Bedfordshire	Bracknell Forest
Luton	54399	1071	865	6876	28
Mid Bedfordshire	3961	29925	5675	1662	30
Bedford	1888	4458	50165	599	17
South Bedfordshire	9446	987	716	27556	43
Bracknell Forest	12	0	8	6	30840

Matrix $\tilde{C}$ corresponding to Districts listed in table A1:

The proportions of commuters travelling from District i to work in each of the N Districts

$\tilde{C} =$	0.6624	0.0130	0.0105	0.0837	0.0003
	0.0623	0.4706	0.0892	0.0261	0.0005
	0.0269	0.0634	0.7137	0.0085	0.0002
	0.1654	0.0173	0.0125	0.4824	0.0008
	0.0002	0.0000	0.0001	0.0001	0.5156

Matrix *W* corresponding to Districts listed in table A1:

Same as $\tilde{C}$ but the leading diagonal cells are set to zero prior to standardisation (the frequency in each row divided by the row total).

$W =$	0.0000	0.0386	0.0312	0.2480	0.0010
	0.1176	0.0000	0.1686	0.0494	0.0009
	0.0938	0.2215	0.0000	0.0298	0.0008
	0.3195	0.0334	0.0242	0.0000	0.0015
	0.0004	0.0000	0.0003	0.0002	0.0000

List of variables used in the study.

(Note that the table only includes variables that the paper defines without using equations. The rest are defined in the main body as they are introduced.)

	Model
I	income within commuting distance
E	The number of workers
w	Average wages
p	Average house price
i	District
t	Time period (year)
$\tilde{C}$	*N* by *N* matrix in which row *i* (*i* = 1,…,*N*) contains the proportions of commuters travelling from District *i* to work in each of the *N* Districts
W_N	*N* by *N* matrix based on commuting frequencies, with zeros on main diagonal, and row normalised so that rows sum to 1.0
S	Stock of dwellings
B	Bank of England interest rate
F	FTSE ALL SHARES index
ω, ς	Random disturbances of demand and supply equations
	Parameters of dynamic spatial panel specification
γ	Coefficient of the temporal lag of price
ρ_1	Coefficient of the spatial lag of price
β_1	Coefficient of income
β_2	Coefficient of dwelling stock
β_3	Interest rate coefficient
β_4	Share index coefficient
θ	Coefficient of the spatial lag of the temporal lag of price
ρ_2	Coefficient of the autoregressive spatial error process
σ_μ^2	Variance of the time-invariant error component
σ_ν^2	Variance of the transient random disturbance
μ	Time invariant error component accounting for unobserved sources of heterogeneity across district
υ	Transient error component accounting for unobserved spatial and temporal effects