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Delineating the Spatio-Temporal Pattern of House Price Variation by Local Authority in England: 2009 to 2016

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Housing is a major source of inequality in England, but most house price variation studies are conducted at national or regional scale or, conversely, in a specific city. Detailed research at sub-regional level is missing, especially for the period after the global financial crisis. This research addresses this gap with an analysis of variation at local authority level across England between 2009 and 2016. A novel house price per square meter (HPM) dataset is used to control for property size effects in transaction price variation. The effects of two spatial levels (local authority (LA)—and Middle Layer Super Output) together with three time categorizations (quarterly, half-yearly, and yearly) is systematically explored using multilevel models. Results show that the time categorization effects are essentially identical and extremely small, in comparison with the LA effects. As annual effects provide the best model fit, LA annual house price trajectories are explored further. Overall higher HPM LAs grew faster over the 8-year period than lower HPM LAs. [Corrections made on 05 May 2022, after first online publication: '80-year' in the previous sentence has been corrected to '8-year' in this version.] More locally the spatial pattern shows some variation in the overall pattern, with some LAs near London or Bristol exhibiting higher relative percentage HPM increases with a relatively lower initial HPM compared with their neighbors.

Introduction

A house is an immovable asset and aside from its physical attributes, its location is regarded as the most important determinant of its value (Kiel and Zabel 2008; Downes 2018). House prices in desirable locations are frequently too high to be affordable for people on average salaries and, in countries such as the United Kingdom, exhibit large spatial disparities (Hamnett and Reades 2019). However, commentary on this spatial heterogeneity in the UK is often fairly crudely expressed through observations such as the "North-South divide." The modeling of English house price changes dates back to the 1970s (Ball 1973; McAvinchey and Maclennan 1982). This

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research explored the variation at coarse scales such as regions or, conversely, in a specific city. The city-based research mainly focused on exploring the determinants of the spatial and temporal variation of property prices rather than the house price trends themselves. Regional house price spatio-temporal patterns and fluctuations have been well explored and historically conceptualized as a ripple effect spreading out from London and the South East across England since 1969 (Meen 1999; Cook 2003; Stevenson 2004; Cook and Watson 2016; Hamnett and Reades 2019), but little sub-regional analysis in the UK has appeared in the literature (Jones and Leishman 2006). This is a particular issue given that housing regulation and delivery in England has been carried out by local authorities (LAs) since the 1880s. Although local authorities have played an increasingly marginalized role in housing markets through a dwindling of social stock after the introduction of the "Right to Buy" in 1980 (Morphet and Clifford 2020), they still play a crucial role in planning policy and decisions and thus make them a scale of analysis highly relevant to any research with relevance to local housing policy. Currently there is a growing move for local authorities to develop housing for sale and rent to bolster their revenues in the face of dwindling government support (Morphet and Clifford 2020). Further, our understanding of house price heterogeneity in England has been limited to the time period after the Global Financial Crisis (GFC) of 2008 whereas most regional house price analyses explore periods before the GFC.

House price data deficiencies in England limit research on house price variation at local level. Much house price research in England has been based on mortgage datasets (e.g., 5% sample survey of Building Society Mortgages or the Nationwide Building Society mortgage data), but this data is just a small sample of the total number of transactions and has potential biases in representing the whole market (Hamnett 1983; Jones and Bullen 1993). Local estate agent survey data avoid this bias but is not widely available across England (Orford 2000). Land Registry Price Paid Data (PPD), published as open data in 2013, narrow this data gap as it offers the most comprehensive set of transaction price records at address level in England; however, it lacks detail on property characteristics. For example, floor area is not available in the PPD which limits its usefulness for price variation analysis where stock characteristics vary so much suggesting it requires enrichment from other data sources (Orford 2010; Powell-Smith 2017; Chi et al. 2019; Lewis 2020). Linking the PPD to other attribute-rich datasets such as the Ministry for Housing, Communities and Local Government's Energy Performance Certificates (EPCs), offers the opportunity to explore house price variation nationally, controlling the floor size effect by using a house price per square meter (HPM) measure.

Another criticism of housing research in England is that there is a lack of research on house price variation at different geographical and temporal scales, especially for the period after the GFC of 2008—a time of great shock in the UK housing system (Gray 2012; Cooper et al. 2013). Some recent studies have begun to address this (Gray 2012; Feng 2016; Orford 2017; Law, 2018; Chi, Dennett, Oléron-Evans, et al. 2020), but only few have carried out this analysis nationally (Gray 2012; Cooper et al. 2013; Feng 2016; Chi, Dennett, Oléron-Evans, et al. 2020) and only Chi, Dennett, Oléron-Evans, et al. (2020) have accounted for the effect of size in transaction price. Two new insights into house price variation emerged from this research: firstly the examination of HPMs at LA level showed almost twice the variation of house price compared with raw transaction price. Secondly, HPMs at LA level represented 53% of England house price variation in 2009, increasing to 76% in 2016, although these changes over time are not fully understood.

LAs in England have a duty to ensure effective functioning of their local housing markets (Morphet and Clifford 2020). A knowledge gap existed in understanding LA house price variation after the economic crisis. To overcome this knowledge gap in this paper we take this analysis further investigating two spatial scales (LA and the Middle Layer Super Output

Area—MSOA—level) and three different time scales (quarter, half-year, and year). The three different time scales are chosen as they are commonly used time slices in analysis house price trend in England. Our two aims were, first, to understand the extent to which space and time influence HPM variation in England and, second, to facilitate a deeper understanding of spatio-temporal changes using a model-based descriptive approach. In Section 2 we briefly review the previously observed house price variation in England and some common spatio-temporal models. In Section 3, the study area and the data used are introduced. Section 4 presents the multilevel modeling approach with the results shown in Section 5. A summary and conclusions are detailed in Section 6, together with recommendations for future research.

House price spatio-temporal variation in England

Regional house price trends in England have been likened to pond ripples after a stone is thrown in (Cooper et al. 2013). This metaphor refers to the notion that high house prices in one region push up house prices in adjoining regions over a time period (MacDonald and Taylor 1993). Empirical studies show such a pattern, with London and the South East being the ripple source leading to eventual spill-overs to other regions (Giussani and Hadjimatheou 1991; MacDonald and Taylor 1993; Alexander and Barrow 1994; Meen 1996). This phenomenon of interregional interactions has been well-identified in long-term house price changes at quarterly or annual time scales since 1968.

Shocked by the GFC of 2007, regional house prices in England were pushed into a two-year recession between 2007 and 2009, with different rates of recovery afterwards. Studies after 2009 not only reveal a similar ripple effect, but also show an unprecedented divergence with an increasing of regional house price differences driven by a faster price increase in London (Cook and Watson 2016; Hamnett and Reades 2019). Gray's (2012) research at LA level for the time period before Global Financial Crisis (1997–2007) showed no "perfect ripple" but a pattern of hot and cold spots fragmented and dispersed across England. It showed, however, that LA house price growth exhibits a spatially and temporally lagged diffusion from the high-price areas in London to more distant areas.

All the above research, however, delivers conclusion based on a non-mix-adjusted index (aggregate transaction price), which will bias the results (Gray 2012). Normalizing the transaction price by using HPM rather than using raw transaction price offers a more reliable basis for analysis (Chi, Dennett, Oléron-Evans, et al. 2020). Additionally, most of this research directly uses quarterly or yearly time categorization. Cooper et al. (2013) attempted to use different time slices when producing aggregate house price indices at different spatial scales, but their approach does not enable a systematic understanding of the time effect on price variations.

Various modeling techniques have been proposed to detect spatio-temporal patterns, such as geographically and temporally weighted regression (Huang, Wu, and Barry 2010; Fotheringham, Crespo, and Yao 2015), spatio-temporal areal unit modeling (Lee, Rushworth, and Napier, 2018), and multilevel modeling (Jones and Bullen 1993, 1994; Orford 2002). Within these three types models, geographically and temporally weighted regression (GWR) has a computational challenge when observation numbers exceed 10,000 (Li et al. 2019), which is the case in our research. Spatio-temporal areal unit modeling relies on areal unit data at a single level to analyze spatial-temporal patterns, but this misses multi-level effects. Multilevel modeling (MLM) is a statistical tool that will allow for these different geographical and time level influences to be captured for a large number of cases and as such is our preferred method here. It also has some other useful advantages as within the groups in any given level, it allows relationships to vary around the overall relationship for all individuals across all the groups (Jones, 1991a). To produce more reliable estimates for groups with small sample sizes, MLM shrinks the estimates toward the overall average (Steele, 2008a).

Study area and data

Study area

The study area is the whole of England, the largest country of the United Kingdom. It contains nine regions: the North East, the North West, Yorkshire and the Humber, the East Midlands, the West Midlands, the East of England, the South East, the South West and London. Administratively, England is divided into 326 LAs, and these are further divided into 6,791 MSOAs.

House price data

We use HPM information from a newly created house price dataset. This is a linked address-level database which uses the HM Land Registry PPD together with property geo-reference information from the Ordnance Survey and total floor area from Domestic EPCs in England between 2009 and 2016. The combining of the above datasets together with data cleaning meant 20% of the full market housing sales in the PPD was removed. Of this, 7% was due to linkage failure and 13% due to missing data or errors the property size information. Although the new dataset only represents 80% of full market housing sales in England from Land Registry PPD, it still covers all the regions, LAs, MSOAs, and 99.99% of Lower Layer Super Output Areas (LSOAs) in England. Nevertheless, 99% of LAs in England have over 80% representation of the Land Registry PPD sales in the new dataset, and 95% of local authorities have over 90% representation. Only three LAs—the City of London, Westminster, and Camden—have less than 80% representation (Chi et al. 2019). The new dataset records 4,682,468 full market sales and six fields are used in this research, namely HPM, transaction year, transaction half-year, transaction year quarter, MSOA codes, and LA district codes.

Methodology

The following analysis is divided into two stages with three methods employed. Firstly, a variance components model is used to explore the space and time effects on house price variance in England between 2009 and 2016, for three different time scales (yearly, half-yearly, and quarterly). Secondly, growth curve models are used to present a model-based description of the spatio-temporal patterns of local house prices in England between 2009 and 2016. Choropleth mapping is used to represent the spatio-temporal patterns of England's local housing markets.

Variance components model

The variance components model is the simplest multilevel model with no explanatory variables (Raudenbush and Bryk 2002; Goldstein 2010). It quantifies variances over different spatial scales and time scales (Jones 1991b). A four-level variance components model was built to explore the extent of house price variation by LA, MSOA, and time. This model is written as:

$$\begin{gathered} hp_{igkj} = \beta_0 + l_j + m_{kj} + u_{gkj} + e_{igkj} \\ l_j \sim N\left(0, \sigma_l^2\right) \\ m_{kj} \sim N\left(0, \sigma_m^2\right) \\ u_{gkj} \sim N\left(0, \sigma_u^2\right) \\ e_{igkj} \sim N\left(0, \sigma_e^2\right) \end{gathered} \tag{1}$$

where hp_{igkj} refers to an individual (natural log scale) observed HPM i, during time period g in MSOA k and LA j. The fixed term β_0 represents the overall mean HPM over the complete time period, and l_j, m_{kj}, u_{gkj}, and e_{igkj} are the random terms of the model, representing respectively the residuals at LA level, MSOA level, time level, and individual level. l_j measures the extent to which the overall mean house price in LA j varies from the overall mean HPM (β_0),m_{kj} measures the extent to which overall mean house price in MSOA k deviates from the overall mean HPM in LA j. u_{gkj} quantifies the difference between the mean HPM for a given time period (e.g., one year) in one MSOA and that MSOA's mean HPM over the whole period. The individual residual e_{igkj} quantifies the difference between any individual HPM and the mean MSOA HPM within the same time period. Residuals at each level are assumed to be independent and identically distributed with a normal distribution of zero mean and constant variance.

In this model, total HPM variance is decomposed into four parts (σ_l^2, σ_m^2, σ_u^2, and σ_e^2), which represents the variance around the grand mean at the level of LA, MSOA, time, and individual (Jones and Bullen 1993). The variance at LA level (σ_l^2) measures HPM differences between LAs over the whole period; σ_m^2 is the MSOA level variance, measuring the price difference within local authority between MSOAs over the whole period; σ_u^2 is the residual variation at time level, which measures the time-to-time (e.g., year-to-year) differences within the same MSOA; σ_e^2 is the individual variance, measuring the HPM variability for a given time period and MSOA. With these four variance components in the hypothetical model, variance partition coefficients (VPC) can be calculated to summarizes the "importance" of spatial and time effects in influencing house price variation. For example, VPC at LA level represents the house price variability that can be accounted for at LA level. The equation for VPC at LA level is presented as equation (2), which is between-LA variance divided by the total variance.

$$\mathrm{VPC}_l = \frac{\sigma_l^2}{\sigma_l^2 + \sigma_m^2 + \sigma_u^2 + \sigma_e^2} \tag{2}$$

VPC ranges from 0 to 1, with 0 signifying no between group differences and 1 signifying no within group differences. A higher VPC at a particular level indicates that a greater proportion of total variation is due to differences between the units at the given level.

Three separate four-level variance components models were used to estimate the extent of the house price (i.e., HPM) variability at LA level and MSOA level and for three different time horizons (quarterly, half-yearly, and yearly) within the study period. Level 1 is the individual residential properties. Level 2 is the quarterly, half-yearly, or yearly time horizon. Level 3 is MSOA level and level 4 is LA level. The equations for these three models are listed in Table 1. Likelihood ratio (LR) tests are used to test the significance of the LA, MSOA, and time effect in Models 1, 2, and 3. The LR test is based on the change in deviance (–2 log likelihood) between two models and has a chi squared distribution (Raudenbush and Bryk 2002). The significance of LA effect is verified by conducting a LR test based on the deviance change from the candidate models in Table 1 to their corresponding three-level variance components models, obtained by dropping the LA level (l_j). The MSOA effect is verified through comparison between the candidate models in Table 1 and their corresponding three-level variance components models by dropping the MSOA level (m_{kj}). The three different time horizon effects are verified by means of three pairwise likelihood ratio tests, comparing the candidate models with their corresponding three-level variance components models, obtained by dropping the given time level (e.g., q_{skj}).

Table 1. The Candidate Four-Level Variance Components Models

Model	Equation
Model 1	$hp_{iskj} = \beta_0 + l_j + m_{kj} + q_{skj} + e_{iskj}$
Model 2	$hp_{iwkj} = \beta_0 + l_j + m_{kj} + hy_{wkj} + e_{iwkj}$
Model 3	$hp_{idkj} = \beta_0 + l_j + m_{kj} + y_{dkj} + e_{idkj}$

Notes: hp is the log scale of HPM. For example, hp_{iskj} stands for the log of HPM i in quarter period s in MSOA k in LA j. β_0 is overall mean house price across the LAs overa the complete time period, l_j is the residuals at LA level, m_{kj} is the residuals at MSOA k in local authority j, q_{skj} is the residual at time level in terms of quarter, hy_{wkj} is the residual at time level in terms of half-year period, y_{dkj} is the residual at time level in terms of year. e_{iskj}, e_{iwkj} and e_{idkj} are stand for individual level residuals.

Additionally, the lowest deviance is used to identify which four-level variance components models is the best fitted model in Table 1.

Growth curve modeling

Growth curve modeling generally uses a multilevel model with time as a predictor to fit a trend in repeated-measures data over time and across different levels (Goldstein 2010). Growth curve modeling has been effectively used in longitudinal studies when addressing questions about change (Singer and Willett 2003; Steele 2008b; Zaninotto, Falaschetti, and Sacker 2009). In house price analysis, house price can be treated as a "repeated measurement" for the same areas (Jones and Bullen 1993). For example, individual transaction prices (level 1) are recorded for different LAs (level 2). Such a basic two-level growth curve model can be represented formally using the following equation:

$$\begin{gathered} hp_{ij} = \beta_0 + \beta_1 t_{ij} + l_j + e_{ij} \\ l_j \sim N\left(0, \sigma_l^2\right) \\ e_{ij} \sim N\left(0, \sigma_e^2\right) \end{gathered} \tag{3}$$

where hp_{ij} is the individual HPM (natural log scale) for the ith transaction in LA j, t_{ij} is the time (e.g., year) of the transaction i in LA j. The natural logarithm of the response is used to reduce problems of non-linearity and provides a meaningful interpretation of the estimated slope parameter β_1. β_1 is the overall average slope. For small values of β_1, it is approximately equal to the overall percentage change in HPM (Tufte 1974). β_0 is the overall mean, which is interpreted as the overall HPM in England (2009–2016) in terms of a logarithmic scale. The fixed part is $\beta_0 + \beta_1 t_{ij}$, the random part is $l_j + e_{ij}$. l_j and e_{ij} are the residuals. Residuals at the same level or different levels are assumed to be uncorrelated.

In equation (3), all the LAs in level 2 share the growth trend (β_1). However, growth curve modeling can permit this growth to vary between LAs by adding a new random part $l_{1j}t_{ij}$. The new equation is:

$$\begin{gathered} hp_{ij} = \beta_0 + \beta_1 t_{ij} + l_{0j} + l_{1j} t_{ij} + e_{ij} \\ l_{0j} \sim N\left(0, \sigma_{j0}^2\right) \\ l_{1j} \sim N\left(0, \sigma_{j1}^2\right) \\ e_{ij} \sim N\left(0, \sigma_e^2\right) \end{gathered} \tag{4}$$

Here, hp_{ij}, β_0, β_1, and e_{ij} have the same meaning as in equation (3). l_{0j} has the same meaning as l_j in equation (3). The new random term l_{1j} measures the extent to which the slope of LA j deviates from the overall slope β_1. The random effects l_{1j} and l_{0j} are assumed to follow normal distributions with zero mean, variances σ^2_{j0} and σ^2_{j1} respectively, and covariance σ_{j01}. e_{ij} is also assumed to follow a normal distribution with zero mean and constant variance σ^2_e.

Figure 1 provides a graphical illustration of equation (4) for 22 transactions in two LAs (LA a and LA b) in England over five consecutive time intervals. Individual HPMs are shown as a black circle. β_0 is the intercept, which represents the grand mean HPM (log scale) in England at time 0. β_1 represents the overall slope in England across the whole time period, which is approximately equal to the percentage change of the HPM (Tufte 1974; Jones and Bullen 1993). $\beta_0 + l_{0j}$ measures the intercept for LA j, and $\beta_1 + l_{1j}$ measures the HPM percentage change for LA j. LA a has a larger intercept value ($\beta_0 + l_{01}$) than the mean HPM in England (β_0) with a positive l_{01}, whereas LA b has a smaller intercept value ($\beta_0 + l_{02}$) than the mean HPM in England with a negative l_{02}. The slope of LA a ($\beta_1 + l_{11}$) is steeper than the overall average slope line (the black line) by an amount l_{11}, whereas LA b has a slope ($\beta_1 + l_{12}$) which is smaller by an amount l_{12}. For the HPMs in LA a and LA b, a high intercept is associated with a steep slope. If this pattern holds when all LAs are considered, the intercept-slope covariance will be positive and the group lines (the blue solid lines) will "fan out." e_{ij} measures HPM differences for each individual i over the intercept (average LA HPM at time 0).

Given that house prices within the same MSOA are more similar than the HPMs within the same LA (Chi, Dennett, Oléron-Evans, et al. 2020), we account for MSOA effects in the model by adding in MSOA level in the random part. Equations (3) and (4) can be extended to a three-level

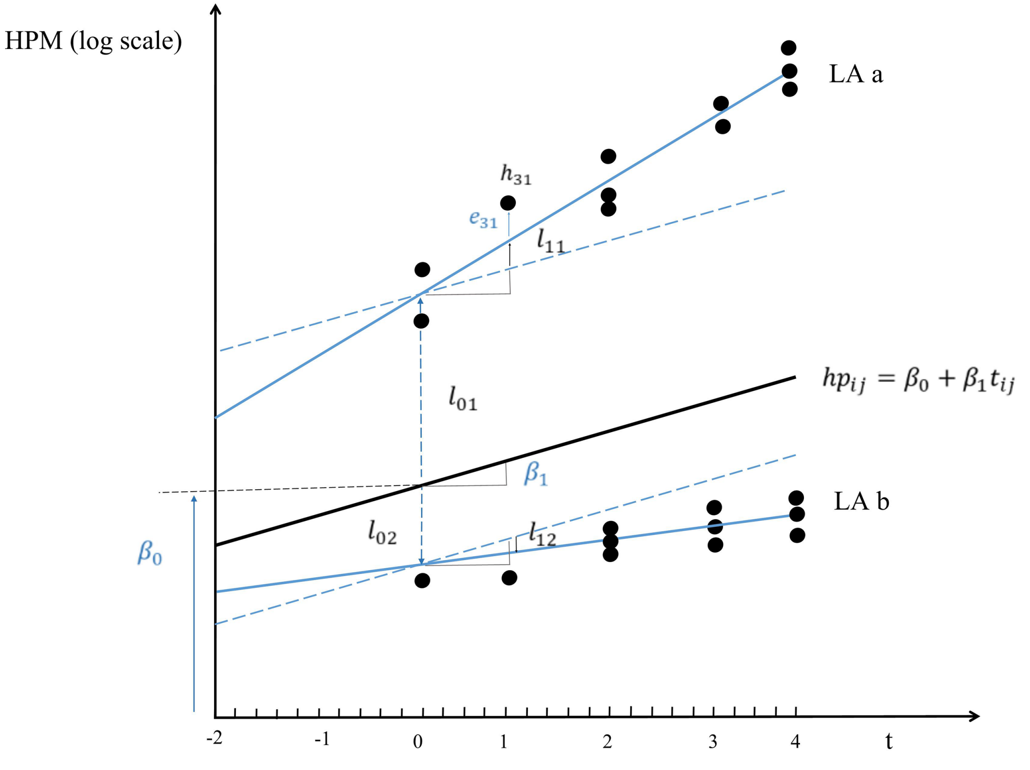

Figure 1. A graphical illustration of the two-level growth curve model in equation 4. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 2. The Candidate Three-Level Growth Curve Models

Model	Equation
Model 4	$hp_{ikj} = \beta_0 + \beta_1 t_{ikj} + l_j + m_{kj} + e_{ikj}$
	$l_j \sim N\left(0, \sigma_l^2\right)$
	$m_{kj} \sim N\left(0, \sigma_m^2\right)$
	$e_{ikj} \sim N\left(0, \sigma_e^2\right)$
Model 5	$hp_{ikj} = \beta_0 + \beta_1 t_{ikj} + l_{0j} + m_{kj} + l_{1j} t_{ikj} + e_{ikj}$
	$l_{0j} \sim N\left(0, \sigma_{l0}^2\right)$
	$l_{1j} \sim N\left(0, \sigma_{l1}^2\right)$
	$m_{kj} \sim N\left(0, \sigma_m^2\right)$
	$e_{ikj} \sim N\left(0, \sigma_e^2\right)$

Notes: hp_{ikj} is the log HPM for transaction i in MSOA k belonging to LA j. t_{ikj} is the time period of the corresponding transaction, time scales is choose according related time scales of the best fitted model among models 1 to 3. β_0 is overall mean house price across all LAs between 2009 and 2016, β_1 is the slope, l_j or l_{0j} is the residual at level 3, m_{kj} is the residual at level 2, e_{ikj} is the residual at level 1. l_{1j} is the random slope at level 3.

growth curve model by adding in a random term m_{kj} as two models are listed in Table 2. In Models 4 and 5, Level 1 is individual, level 2 is MSOA level and level 3 is LA level. A LR test is used to compare Models 4 and 5 to determine which provides a better fit. If Model 5 fits the data better, LAs in England reveal different house price growth curves compared with Model 4.[1] The time variables (t_{ikj}) are centered at the beginning of year 2009 so that the estimated intercept has a meaningful interpretation (Raudenbush and Bryk 2002), as the estimated house price (log scale) in 2009. We refer to the estimated slope for each LA in Model 4 and Model 5 as "estimated HPM percentage change" (LA slope, such as β_1 in Model 4 or $\beta_1 + l_{1j}$ in Model 5). We transform estimated intercept to its nature scale for each LA (e.g., exponential $\beta_0 + l_{0j}$ in Model 5) and refer to it as the "starting-price."

Results and discussion

Models 1 to 5 were run in MLwiN 3.03 (Charlton et al. 2019) using the Iterative Generalized Least Squares (IGLS) algorithm. The LR test on LA, MSOA and time random effects for each of the Models 1 to 3 are associated with effectively zero p-values, revealing that LA, MSOA and time variance are separately significant in these three models. Similarly, the LR test on LA, MSOA effect in Models 4 and 5 also results in a separately effectively zero p-value. Meanwhile, Model 3 with the lowest deviance among the Models 1 to 3 reflects the best fit model in the four-level variance models. We therefore choose the year as time scale in Models 4 and 5. A LR test reveals that Model 5 is preferred over the Model 4 (LR = 175,386, $P < 0.001$). All the results discussed below are based on the estimated values from these five multilevel models. Choropleth maps are plotted in ArcGIS 10.6.

LA and time effects on HPM variation in England (2009–2016)

Table 3 presents the VPC results of the three four-level variance components models. For all three models, the VPC at each level is exactly the same when rounding to two decimal places. There is no difference in the influence of time for the three different time scales (i.e., quarter, half-year, and year) in England HPM variance. Compared with the LA and MSOA effects on

Table 3. VPC Statistic for Model 1, Model 2, and Model 3

Model 1		Model 2		Model 3	
Level	VPC	Level	VPC	Level	VPC
LA level	0.59	Local authority level	0.59	Local authority level	0.59
MSOA level	0.12	MSOA level	0.12	MSOA level	0.12
Quarter level	0.05	Half-year level	0.05	Year level	0.05
Individual level	0.24	Individual level	0.24	Individual level	0.24
Deviance	1,428,443	Deviance	1,338,665	Deviance	1,287,883

Table 4. Model Results of Growth Curve Model

	Model 4		Model 5	
Parameter	Estimate	SE	Estimate	SE
β_0 Intercept	7.5613	0.0237	7.5639	0.0199
β_1 (Year-2009)	0.0386	0.0001	0.0379	0.0013
σ^2_{l0} between local authority variance	0.1806	0.0144	0.1262	0.0102
σ_{l01} Intercept-slope covariance	–	–	0.0061	0.0006
σ^2_{l1} Slope variance	–	–	0.0006	0.0000
σ^2_{m} between MSOA variance	0.0369	0.0007	0.0373	0.0007
σ^2_{e} Individual variance	0.0789	0.0001	0.076	0.000
Deviance	1,438,463		1,263,077	

the total HPM variance, the time effect is very small (only accounting for 5% of total variance). Time is therefore treated as a fixed effect rather than a random effect in all subsequent analysis. Moreover, the deviance of Model 3 is smallest indicating that the annual time scale is the most appropriate. Therefore, subsequent analysis exclusively uses a one-year time scale.

The VPC at LA level is the greatest (0.59); this indicates that 59% of total HPM variance (log scale) between 2009 and 2016 lies between LAs. In other words, HPM differences between LAs in England are very large and HPM differences within LAs are relatively small. Of total HPM variance 12% lies between MSOAs within the same LA. Of the remaining 29% of variance, only 5% is due to year difference: 25% of total HPM variance occurs at the individual level, this could be due to differences between individual properties after controlling for size (e.g., plot size, property quality).

LA HPM change between 2009 and 2016

Table 4 summaries the model results from Models 4 and 5. Owing to a large decrease in deviance between Model 5 and 4, the LR test gives a near zero *P*-value. This suggests that Model 5 fits the data significantly better than Model 4, which reveals that LAs' HPM growth trends do vary across England.

Covariance between the intercept and slope is 0.0061 in Model 5, suggesting a positive relationship between the LA slope and intercept. In other words, HPMs in expensive LAs grew relatively faster than in cheap LAs between 2009 and 2016. As the slope variance at LA level is also positive (0.0006), a "fanning out" of house price growth trends exists at LA level in England

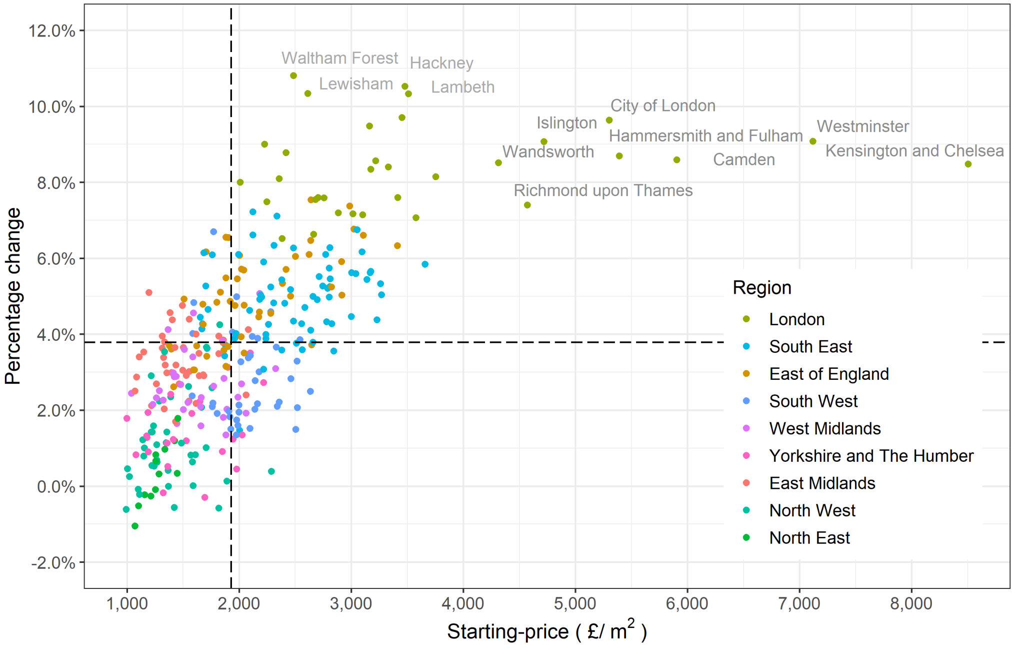

Figure 2. The relationship between LA's starting-price and percentage change in Model 5. [Colour figure can be viewed at wileyonlinelibrary.com]

over the period (Figure A in Appendix A). Intercept variance (σ^2_{l0}) at LA level is significantly larger than the slope variance (σ^2_{l1}), revealing a large difference in HPMs in 2009 across LAs and a very small difference in the overall HPM percentage increase across LAs. Figure A shows the estimated growth curves for each LA in Model 5 and each solid line stands for one LA. The blue lines represent the boundary of the fanning out trend. The dashed black line reflects the estimated HPM trend. LAs represented in the top eight lines show a clear cluster continuing far away from the overall HPM trend level, following by some LAs hold highest house price increase.

To further explore this growth trend, Figure 2 is created from Figure A by plotting the intercept and slope for each line. The intercept has been transformed back to its natural scale for each LA, and thus refers to the estimated starting-price in 2009. Each point stands for one LA and is colored by region. The black dashed lines indicate the England's starting-price in 2009 (1,927 £/m^2) and its overall HPM percentage change between 2009 and 2016 (3.79%). It is obvious that the fanning out is not as simple as HPMs in expensive Las, which grew relatively faster than in cheaper LAs between 2009 and 2016. The top eight most expensive LAs (Kensington and Chelsea, Westminster, Camden, City of London, Hammersmith and Fulham, Islington, Richmond upon Thames and Wandsworth), having HPM over 4,000 £/m^2 in 2009, show a greater than 8% price increase in the following seven years. But they did not display the highest HPM percentage increase. The City of London displays the highest HPM percentage increase in this cluster, but this ranks only fifth among the LAs in England. The top four highest percentage increase LAs (Waltham Forest, Hackney, Lewisham and Lambeth) exhibit a higher than 10% HPM increase.

The LAs with a starting-price and percentage increases above the England average (top-right quadrant of Figure 2) show quite diverse behavior compared with all other LAs. Within this group nearly all are within London, the South East, and the East of England. These two dimensions in house price trend are separately plotted as y axis by region in Figure 3. The *x* axis in Figure 3 is the LA's rank order based on the y value, and the dashed lines represent the England wide level of the y value. Obviously, the big differences of LAs within London are the core contribution for the LAs' variation in starting-price and percentage change. Looking at the LAs' HPM percentage increase, London's LAs exhibited increases of greater than 6% between 2009 and 2016, which is far greater than the England level (3.79%). The majority of LAs in the East of England and the South East exhibit moderate increases from 3.79% to 7.6%. Only the Isle of Wight shows relatively small price increases (1.47%) compared with the rest of LAs in South East. LAs in the South West, West Midlands, and East Midlands saw small increases at around the average level for England, between 2% and 6%. With the exception of Trafford, the remaining LAs in the North West and Yorkshire and The Humber saw small percentage increases, below England's average. LAs in the North East saw only very small HPM changes; generally below 2% with fewer LAs show a decreasing overall price change. Meanwhile, the LAs' starting-price pattern within the same region shows a slightly different pattern as LAs' HMP percentage increases. For example, the Isle of Wight shows a similar starting-price to the rest of LAs in South East, but it has a relatively small percentage increase. LAs in East Midlands generally have starting-prices below the England level, but the HMP percentage change in some LAs is over the England level.

Spatial pattern difference in LA's starting-price and percentage increase

Figure 4 shows the spatial pattern of average HPM percentage increases across LAs in England between 2009 and 2016. LA HPM percentage changes are sorted into six classes, corresponding to the vertical axis in Figure 2. Given all LAs with higher than 8% HPM increases are in London, we did not further subclassify this group. There are two obvious gradient patterns of percentage change at LA level. One is centered on London and the other is centered on Bristol.

In London and its nearby housing market, house price percentage changes follow a kind of radial gradient pattern with high increases at the center of London, decreasing as distance from the center increases. However, nine LAs (labeled on the inset map in Figure 4) display exceptional behavior. These nine LAs show a higher percentage increase (over 6%) compared with their neighboring authorities, and their travel time to London is around an hour. The underlying reasons that the housing markets of these nine LAs differ from their neighboring areas are likely to vary from case to case. One potential reason for the high percentage HPM increases in Milton Keynes, Luton, Stevenage and Harlow could be their role as London commuter towns; these areas have a high proportion of people who work in London (Appendix B). The reasons for the higher percentage increases in Oxford and Cambridge could be due to local green belt planning constraints or their status as prestigious university towns (Mace et al. 2016; Smith 2017) within relatively easy commuting reach of London. Higher percentage HPM increases in Reading and Bracknell Forest may be due to their technology industries and the fact that both are well-connected to London by both the M3 and M4 motorways, as well as fast rail links (Osborne 2016; Hodson 2019; Holland 2019). Indeed alongside Crawley in Sussex which also displays higher percentage HPM increases, many of these residential areas were developed in the post-war wave of new town building designed to re-house London families and have always retained an association with London through these displaced populations and commuting links.

HPM percentage change in and around Bristol exhibits another radial gradient pattern, with a high increase in Bristol and a decreasing percentage change away from the center, as seen

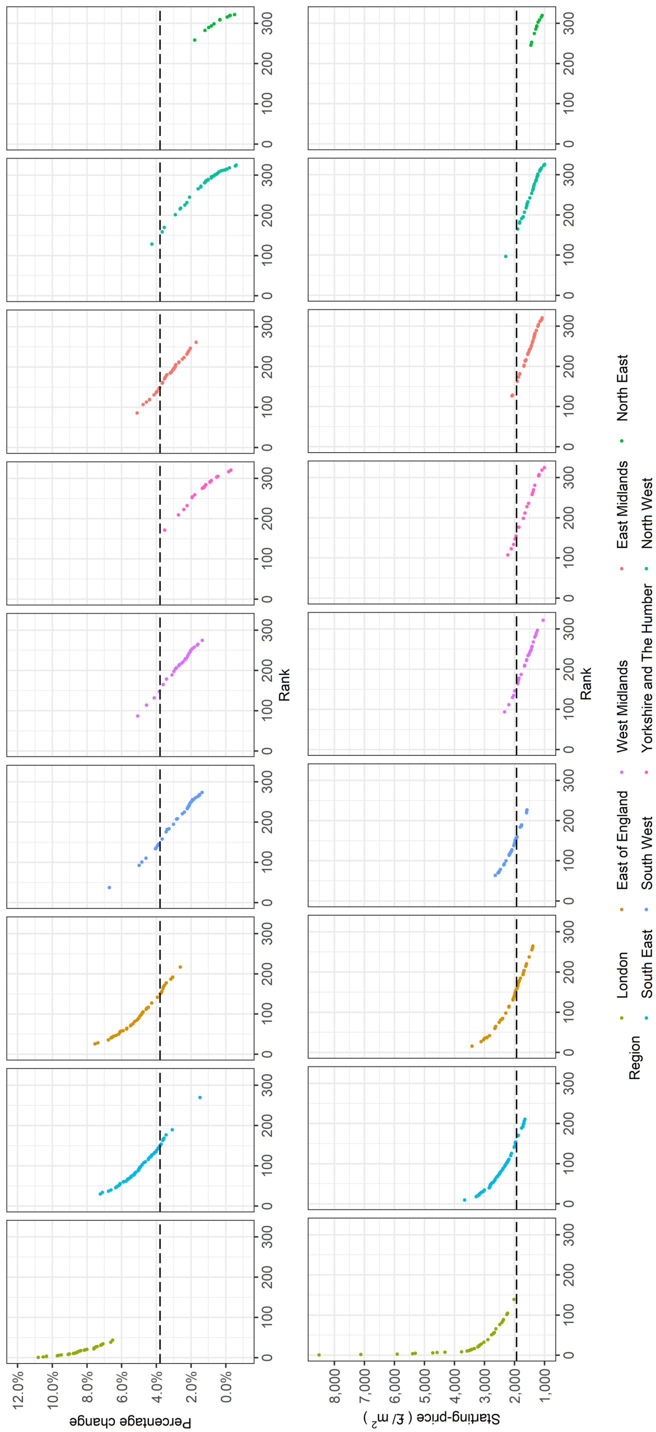

Figure 3. LAs' starting-price and percentage change in England by region. [Colour figure can be viewed at wileyonlinelibrary.com]

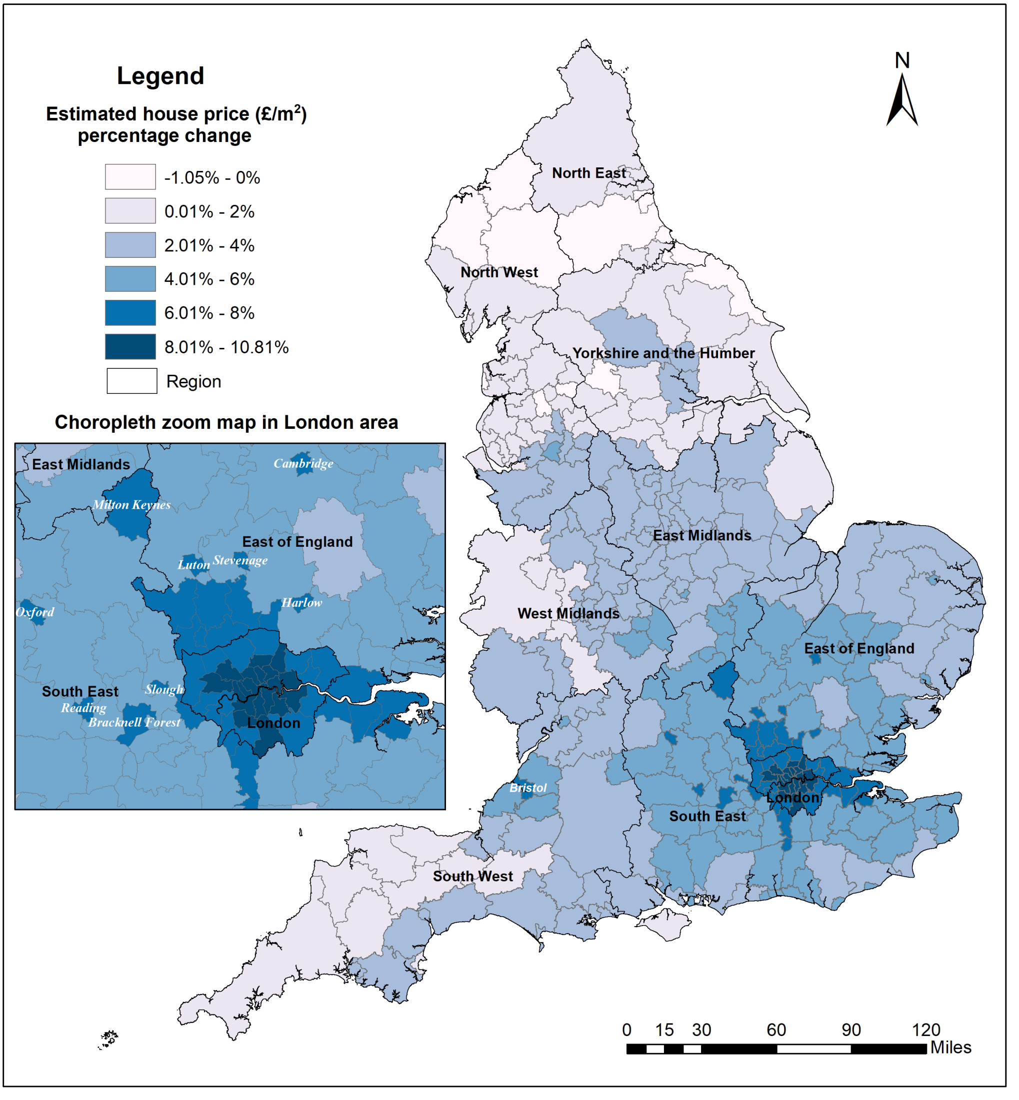

Figure 4. The spatial pattern of overall average house prices percentage change at local authority level. [Colour figure can be viewed at wileyonlinelibrary.com]

in Figure 4. Bristol is a tech hub for the electronics, creative media, and aerospace industries (Card 2014; Ismail 2018). The pattern observed around Bristol may relate to commuting to work patterns, in the same way that the London effect appears to (Rae 2017). Bristol may also be influenced by London as it commutable to London within 75 mins (Chi, Dennett, Morphet, et al. 2020).

Figure 5 represents the spatial pattern of the starting-price at LA level, corresponding to the equal 1,000 £/m^2 interval in Figure 2. Given only two LAs show starting-price over 6,000 £/m^2, we did not further sub-class these two LAs. About 89% of LAs in England have starting-prices between 1,000 and 3,000 £/m^2 level, with 37% of them are over the 2,000 £/m^2 level. Thirty-five of remaining LAs, representing almost 11%, have starting-prices over 3,000 £/m^2. These thirty-five LAs are all located in or near London. Comparing the spatial patterns observed in Figures 4 and 5, Luton, Stevenage, Harlow and Slough exhibit relatively higher percentage HPM increases but relatively lower estimated mean HPM in 2009 compared with their neighbors. LAs near Bristol show high HPM percentage increases, but their starting-prices are not as high as those in London and its nearby housing market, as the zoom map shows in Figure 5.

Looking at the geography of the estimated starting-price at LA level, HPMs display more complex patterns than would be suggested by the simplistic notion of a "North-South divide." In the south of England, fourteen LAs on the southeast coastline and southwest coastline have HPMs under 2,000 £/m^2, relatively cheaper than nearby LAs: Dover, Eastbourne, Gravesham, Hastings, Shepway, Medway, Swale, Thanet, Southampton, Gosport, Portsmouth, Weymouth and Portland, Havant, and Torbay. Conversely, in the North of England, five LAs display higher HPMs than their neighbors, with HPMs over 2,000 £/m^2: Derbyshire Dales in the East Midlands, South Lakeland in the North West, and Hambleton, Harrogate and York in Yorkshire and The

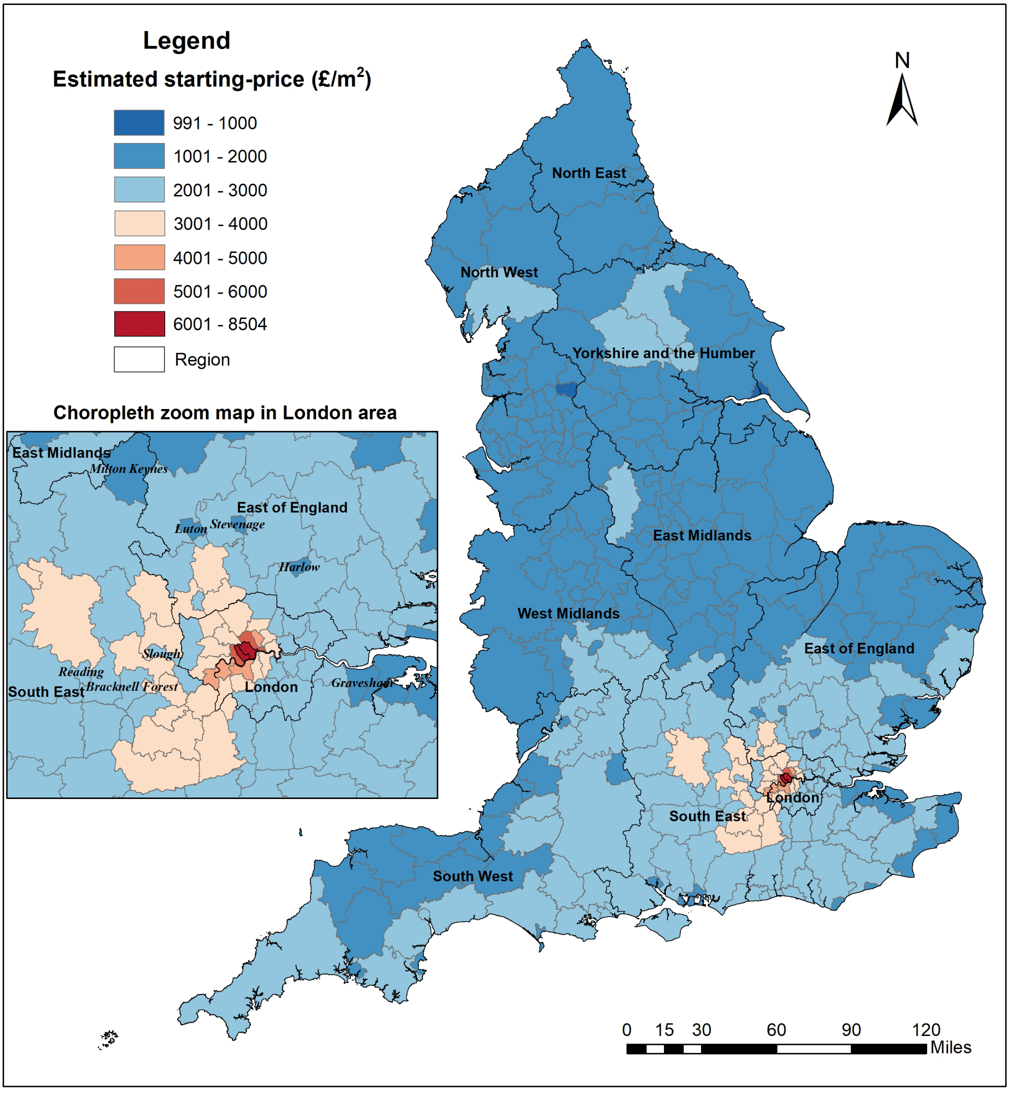

Figure 5. The spatial patterns of local authority starting-price in 2009. [Colour figure can be viewed at wileyonlinelibrary.com]

Humber. Burnley in the North West and the City of Kingston upon Hull in Yorkshire, and The Humber exhibit house prices below 1,000 £/m^2. The estimated mean HPMs of all other LAs in the north of England lie between 1,000 and 2,000 £/m^2.

Conclusions

This research takes a first step in systematically exploring the spatio-temporal pattern of HPMs at LA level in England between 2009 and 2016, something that has not previously been possible due to the absence of data normalized by total floor area. It contributes to house price variation research in three main ways: first, it investigates patterns of HPM variation in England across two spatial scales and three different time scales (quarter, half-year, year) between 2009 and 2016. Results reveal that the two spatial effects on HPM variation are very much larger than any of the time effects. The LA effect contributes 59% of total HPM variance between 2009 and 2016, with the MSOA effect within the same LA contributing a further 12%. The time effect on HPM variance is the same no matter which time scale is used (quarter, half-year, year) and is relatively small enough to ignore compared to the two spatial effects.

Secondly, as a one-year time scale has been found to fit the model best, annual HPM trajectories in England were further investigated using growth curve modeling. Results demonstrate that HPMs at LA level shows a fanning out trend with those LAs that had higher HPMs in 2009 growing relatively faster over the eight-year period than cheaper LAs. Thirdly, the spatio-temporal patterns of HPM at LA level after 2009 are more complex than the previously noted regional "ripple effect," although London's influence still dominates the scene. Bristol is the only other city in England with high percentage price increases not apparently spatially auto-correlated with those local authorities in the immediate orbit of the Capital. Accounting for some aspects of stock heterogeneity through HPM removes some of the obvious "North-South divide" patterns apparent in raw price comparisons, with some LAs exhibiting lower prices than their neighbors and pockets of relatively higher starting-prices in areas in the rural North (South Lakeland, Derbyshire Dales, Harrogate) and South-West (Dorset, Devon and Cornwall) traditionally favored by those (predominantly London-dwellers) who own second homes. Some commuter towns in the London hinterland (Luton, Stevenage, Harlow and Slough) exhibit relatively higher percentage HPM increases but relatively lower estimated HPM in 2009.

The current government's housing policy focuses on numbers of dwelling units without specifying type or space (Wilcox, Perry, and Williams 2014; Stephens et al. 2020). This reflects in part the relative absence of space in the government's definition of a decent home (Department of Communities and Local Government 2006) which mentions only the need for a kitchen to have adequate space for cookers etc. The ability to analyze housing space standards against household size/structure at lower than LA level should enable a more effective analysis of housing conditions and policy implementation than hitherto. Therefore, with a clear understanding of the spatio-temporal patterns of LA house price, we intend to extend this work in two directions. First is developing further understanding of how house price variations by different property types shape affordable property size among LAs and are shaped by London commuting times. Second, we will focus on how the key local factors such as property type, plot size, land use structure, housing density and local physical and socio-economic environments (Narayan and Narayan 2011; Orford 2017; Hudson, Hudson, and Morley 2018) influence HPM variation at LA level between 2009 and 2016. Understanding the underlying mechanisms of house price variation in England at and below LA will not only offer deeper insights into pressing housing inequality issues, but could also inform current housing and planning policies to ameliorate issues of housing inequality.

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Conflict of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Notes

1 Model 4 fits better than its corresponding three-level variance components model (deviance is 1,964,419) according to the Likelihood Ratio test. Also, as the variance in slope observed between MSOAs within the same LA is quite small (0.0001). This reveals that the house price growth trend is quite similar within the same LA. So MSOAs were not modeled with a random slope in subsequent work. Additionally, given the time period in this research is relatively short and the conclusions are roughly similar when we use a quadratic term in time, we use only the linear growth curve model in this research.

2 Data for this map is aggregated travel to work data (Table WU03EW) in the Census 2011 at local authority unit and then treated all the local authorities in London as one unit. The proportion of extra-local authority commuting that goes to London refers to the number of people commuting outside of home local authority to work in London divided by the number of people commuting outside of home local authority to work.

APPENDIX A

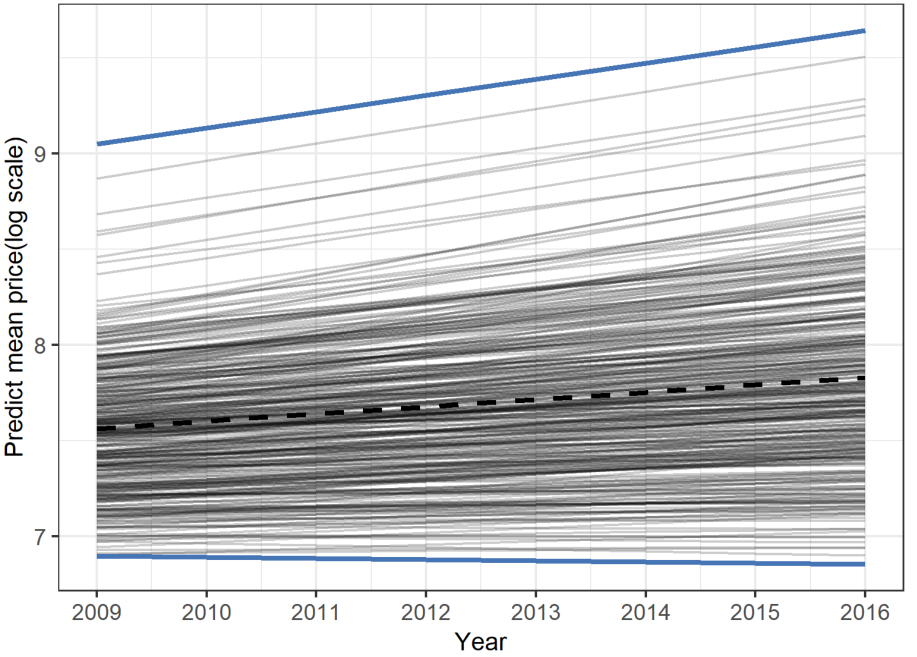

Figure A. The "fanning out" of local house price growth trends across England. [Colour figure can be viewed at wileyonlinelibrary.com]

APPENDIX B

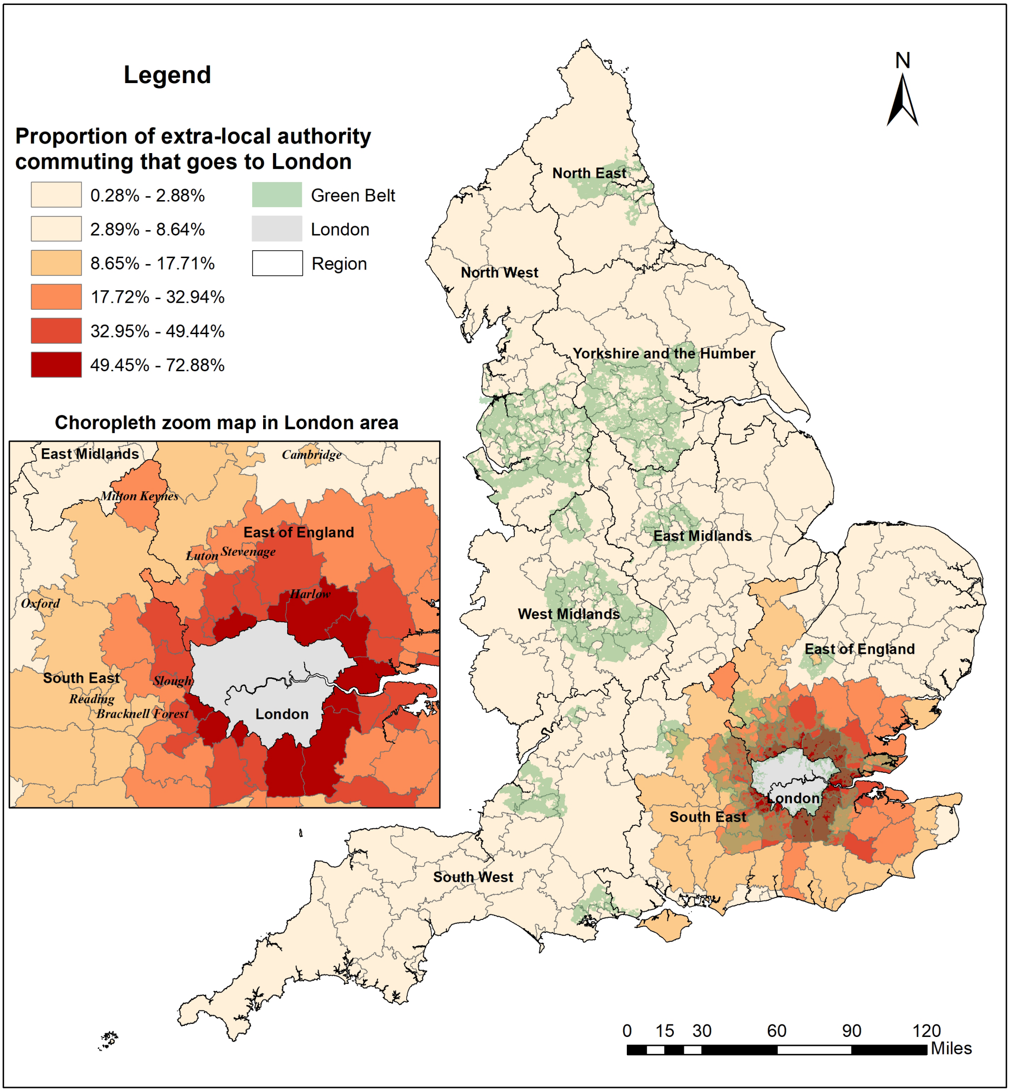

Figure B. Percentage of outside travel to work in London against the total outside travel to work.[2] [Colour figure can be viewed at wileyonlinelibrary.com]

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