Understanding Housing Market Spillovers: Migration, Sentiment and Information Acquisition

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Abstract

Prices and liquidity are closely related in residential real estate markets, both at local level and across neighbourhoods. In this paper, I provide empirical evidence for spatial correlation in housing market turnover, controlling for the role of migration flows. Using micro-level panel data on household valuations of their own non-traded properties, I find that perceived house price growth rates are strongly linked to developments in neighbouring areas, consistent with a framework in which spillovers arise through spatial learning. These mechanisms have the potential to explain the regional clustering of house prices, boom-bust phenomena, feedback effects in housing market liquidity, and the aggregate transmission of shocks from narrow segments of the market.

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1 Introduction

National housing markets lie at the interplay of long-term financial planning decisions by economic agents, policy makers' objectives and risk management practices of financial institutions. However, the heterogeneous nature of public amenities, low supply elasticity and pronounced information asymmetries result in significant limits to arbitrage and persistent disparities across geographical regions. Housing markets are therefore best viewed as being composed of distinct and segmented islands, linked through correlated exposures to economic conditions and complex spatial dependencies in terms of migration, capital transfers and information flows[1]. Price pressure originates in certain segments of the market and tends to spill over across the spatial dimension, ultimately affecting aggregate developments[2].

The established view is that local fundamentals and expectations of fundamentals have limited ability to account for such contagion effects across regions. In this paper, I argue that in order to understand the spatial dynamics of housing markets, there is a need for a broader perspective that also explicitly models regional patterns of co-movement in liquidity. Despite the tight relationship between prices and liquidity at aggregate level, the nature and role of the spatial dynamics of liquidity is little understood. It is this gap that I address, by using disaggregated regional transaction-level data and an explicit spatial framework.

A robust body of empirical research has documented the fact that liquidity and prices are inextricably related. Trading activity is more intense when prices rise and

[1]Lamont and Stein (1999), Mian and Sufi (2011), Gyourko et al. (2013), Piazzesi et al. (2014) and Glaeser et al. (2014) document substantial geographic cross-sectional heterogeneity in house price growth rates, especially driven by the degree to which different regions react to fundamental shocks.

[2]Such phenomena have been widely documented by Basu and Thibodeau (1998), Holly et al. (2010), Brady (2011) and Campbell et al. (2011) and are increasingly shown to be of first-order importance for financial stability. In the context of the recent boom-bust housing market cycle in the US, Mian and Sufi (2009) have prominently traced the origins of the mortgage credit expansion to the relatively small subprime lending sector.

tends to diminish significantly when they fall. Part of the necessary adjustments in response to shocks therefore occurs through the intermediation of market liquidity[3]. If changes in the market structure are indeed leading indicators of housing growth rates[4], spatial correlation patterns should at least partially be attributed to the spatial dependence in market activity.

Moreover, spatial liquidity spillovers are an important and distinct channel for the transmission of information across physical locations. I interpret my empirical findings in the context of the idea that publicly available transaction prices help to coordinate the separate actions of economic agents (Hayek (1945)). In residential real estate markets, buyers face a plethora of unobservable local factors, neighbourhood characteristics and the quality of public amenities, as well as aggregate conditions such as the beliefs, purchasing power and financial vulnerability of other households. The publicly observed set of transactions therefore provides a useful platform for aggregating this information. If the observed set of transactions expands, the uncertainty associated with each individual estimate decreases. Therefore, whenever market liquidity in neighbouring regions is high, agents tend to generate more precise estimates of the house values. This decreases the uncertainty associated with any particular trade, which translates into a higher probability of successful matches and a higher level of local liquidity.

Similar effects are empirically validated at micro level by Alti et al. (2011). They propose a direct measure of rational learning from nearby price signals and show that houses sell 17 percent faster when agents have access to a set of recent sales, compared to the case when this information is not immediately available.

Theoretically, the role of price-mediated information diffusion at neighbourhood level and the interactions of the learning mechanism with the local supply conditions

[3]This co-movement pattern holds at business cycle frequency and within distinct geographical areas, but also seasonally within any given year, as recently described by Ngai and Tenreyro (2014).

[4]This observation has first been made by Miller and Sklarz (1986) and recently documented by Clayton et al. (2010).

have recently been analyzed by Sockin and Xiong (2014). However, to the best of my knowledge, cross-regional informational spillovers have as of yet not been formally looked at in the context of residential real estate markets. In the appendix, I solve a spatial version of the model by Cespa and Foucault (2014), which illustrates the way in which rational learning from price developments in neighbouring areas can lead to spatial correlation in liquidity.

There are a number of alternative causes of spatial dependence in market activity. Cross neighbourhood spillovers can arise as a consequence of household-level labour mobility and the simultaneity between migration and homeownership decisions. Head and Lloyd-Ellis (2012) show that the propensity of home-owners to accept job offers from other regions depends on the turnover of the local housing market, i.e. on how quickly they can sell their houses. Depending on the position in the life-cycle profile and the financial constraints they face, the degree to which households may divest an unwanted property may even be more important than the price at which the transaction can be expected to take place[5]. At the same time, migration is often an opportunity to unlock large funds or extract housing equity, leading to a spatial capital transfer and affecting the liquidity of the destination market.

Also, liquidity can serve as a sentiment indicator, as pointed out by Baker and Stein (2004). In the equity and currency trade literature, sentiment spillovers have been widely documented, both across asset classes and countries. They seem to be a robust feature of the current market environment, especially given the rapid and cheap access to information. For the specific case of residential real estate markets, Soo (2014) shows that the tone of newspaper articles is a powerful determinant of house price expectations, such that measures of sentiment can be used as leading indicators

[5]Demyanyk et al. (2013) discuss recent evidence on the relationship between homeownership and household mobility.

for future price appreciation[6]. In turn, if higher liquidity in neighbouring areas is an indicator of increased sentiment, it should directly affect the beliefs of households, increasing their perceptions about house price growth rates.

Building on the observation that the dynamic spatial dependence of liquidity is a robust feature of the market and it explains part of the widely documented spatial correlation of prices, the main contribution of this paper is to distinguish empirically between these different mechanisms. I first use data on cross-district population movements in order to isolate the mechanical cross-district correlation in transaction levels, which arises as a consequence of population relocation and labour mobility. Second, I use micro-level panel data on household perceptions about house price growth to test the sentiment-based explanation and the empirical implications of a rational framework.

The identifying assumption is that if liquidity acts a sentiment indicator, it affects *average* perceptions of house price growth within a district. If, alternatively, households use the expanded set of transactions in order to learn about underlying fundamental quantities, higher liquidity should lead to a decrease in the *cross-sectional* heterogeneity of perceptions.

The two mechanisms are not mutually exclusive. For example, if the learning process is distorted by extensive media coverage of positive developments, households may also tend to agree more. However, if liquidity does not have a residual role as sentiment in the first place, the decrease in cross-sectional disagreement can be more firmly attributed to rational information acquisition.

I implement the spatial analysis of housing market price and liquidity dynamics at a granular level in England and Wales. Compared to most of the existing literature, I benefit from full coverage of an entire country, with spatially dispersed areas and

[6] The fact that sentiment shocks affect price levels for a period of up to two years matches the much earlier pattern between turnover and prices discovered by Miller and Sklarz (1986). More recently, Soo (2014) confirms that in housing markets the same tight association obtains betweeas sentiment and liquidity, as documented by Baker and Stein (2004) for publicly-traded equity.

substantial demographic, economic and social heterogeneity. To my knowledge, this is the first study to explicitly consider the role of cross-regional migration in a dynamic framework, which allows me to control for the possibility that the observed liquidity co-movements are driven by labour mobility or educational attendance patterns. In so doing, I am able to isolate the residual components which may be driven by information contagion or learning.

My proxy for liquidity is the observed monthly turnover in a given district. This is in line with Clayton et al. (2008), as well as with the usual setup of search models, e.g. Krainer (2001) and Ngai and Tenreyro (2014)[7]. Along the lines of Anselin (1988), I capture the spatial dimension of the effects by using an individual cross-sectional weighting scheme based on the inverse distance between the geometric centres of gravity of two areas.

I find evidence for spatial dependence in market liquidity, which accrues beyond the aggregate dynamics of prices and turnover, as well as controlling for the role of migration flows. The effects are statistically significant at a 1% confidence level. In terms of magnitudes, a one percentage point increase in turnover in nearby regions is associated with a 0.8 percentage points higher local turnover during the next month[8]. Moreover, I show that a significant part of the correlation of prices across sub-markets is due to the co-movement of liquidity: the spatial dependence between growth rates in prices is first estimated to be equal to 0.71 in a simple benchmark setup, and it decreases to 0.13 in the presence of the spatial liquidity effects. Interestingly, the local price-volume correlation seems to vanish, in the presence of spatial dependence,

[7]Our understanding of these phenomena would greatly benefit from a wide-scale country-level dataset on times-on-market, covering a reasonably long time series. However, to the best of my knowledge, such data is not available at the moment either for the UK or another market.

[8]It is tempting to give a causal interpretation to the spatial effects I uncover. However, the results can only be seen as suggestive evidence for the transmission of liquidity shocks. Gibbons and Overman (2010) highlight the numerous challenges faced by any identification scheme, in the context of my dynamic spatial approach.

indicating that housing liquidity cycles have a strong regional component, beyond the trends at national level.

The evolution of individual perceptions about house price growth indicate that households possess substantial information about the value of their homes, despite the inherent thinness of the market and the fact that most properties are not subject to transactions over relatively long periods of time.

The estimation results suggest that the liquidity dynamics in neighbouring districts does not materially influence average perceptions. However, the more intense market activity seems to be associated with lower perceived uncertainty and less cross-sectional disagreement. This is consistent with the hypothesis that households use the observed set of transactions in neighbouring regions in order to learn about unobserved price developments.

Interestingly, general pessimism about financial matters is closely linked with negative perceptions about house values. Since no such relationship obtains on the positive side, this asymmetry is potentially magnifying the effects of the widely documented disposition effect of households.

The paper is organized as follows. Section 2 gives an overview of my methodology and empirical approach. Section 3 describes the primary sources and structures of the different data sets. Section 4 presents the main results, including the suggestive observations on the nature of the shocks affecting the housing market during the sample period. Finally, Section 5 provides concluding statements and indicates important directions for further research. An online appendix, Badarinza (2014), provides a set of summary statistics and additional details about the data sources and econometric procedures.

2 Methodology

2.1 Spatial dependence in housing market activity

The units of observation in this study are the 348 Local Authority Districts in England and Wales, for which I record housing market developments at monthly frequency, through the period 1995 to 2013.

I follow Clayton et al. (2008) and operationalize the concept of liquidity by using a measure of turnover. I denote turnover in period t and district i by $V_{i,t}$ and calculate it by using the observed transaction volume $TV_{i,t}$, divided by the total stock of residential properties per district S_i :

$$V_{i,t} \equiv \frac{TV_{i,t}}{S_i}.$$

In order to understand the magnitude of the bilateral dependence across districts, I use a panel estimation framework which includes a spatial (recursive-) lag of $V_{i,t}$, as described in Anselin (1988). This captures the dynamic dependence between market turnover in neighbouring regions.

For each district $i \in \mathbb{D}$, the weighted turnover in neighbouring areas is defined as:

$$V_{i,t}^{*} \equiv \sum_{j \in \mathbb{D}} \omega_{ij} V_{j,t}.$$

The effect of the migration patterns is captured by the migration flow into and out of area i in period t, denoted by $M_{i,t}$. The benchmark empirical model of cross-district spatial dependence is then given by:

$$V_{i,t} = \mu_i + \delta_t + \rho V_{i,t-1} + \rho^* V_{i,t-1}^{*} + \gamma \Delta P_{i,t-1} + \gamma^* \Delta P_{i,t-1}^{*} + \varphi M_{i,t} + \boldsymbol{\zeta} \mathbf{F}_{i,t-1} + \varepsilon_{i,t}. \quad (1)$$

In equation (1), μ_i are location-specific fixed effects. They eliminate the effect of regional housing market characteristics, such as structural features of the housing stock, particular traits of the environment, as well as the social, demographic and economic composition of the population. Analogously, the time fixed effects δ_t absorb all aggregate variation of market turnover, such that the correlation effects captured by the coefficient ρ^* are purely driven by the local spatial dependence across districts[9]. I denote by $\Delta P^*_{i,t}$ the spatially weighted average of price changes:

$$\Delta P^*_{i,t} \equiv \sum_{j \in \mathbb{D}} \omega_{ij} \Delta P_{i,t}.$$

This specification includes the lagged changes in house prices $\Delta P_{i,t-1}$ and $\Delta P^*_{i,t-1}$, in order to control for any behavioural feedback effects from price developments on transaction volumes. This term is calculated using hedonic-adjusted local price indexes, based on transaction-level data. The respective list of characteristics, as reported by the Land Registry, is given in the online appendix.

To account for any remaining cross-sectional dependence and serial correlation in the error terms, I report robust Driscoll-Kraay standard errors for all dynamic panel estimation specifications. I assess the robustness of the results by allowing for complete spatial dependence in the error term and using a maximum-likelihood procedure. Also, I consider alternative specifications allowing for region $\times$ time fixed effects, and estimate equation (1) sequentially, by eliminating specific regions, e.g. London and Wales. The qualitative nature of all results remains unaffected, across all robustness exercises.

[9] Elhorst (2003) shows that in this class of spatial models the large sample properties of the fixed-effects estimator continue to hold and the model can be estimated by linear least squares, if the coefficients on the fixed effects are not of direct concern. The results are unaffected when using an alternative maximum-likelihood estimation procedure.

2.2 Sentiment and learning at household level

In a second part, after having established that spatial spillovers in market turnover are indeed an important characteristic of the housing market, beyond the usually documented spatial correlation of prices, I explore alternative explanations for the finding. Specifically, I use household-level panel data in order to discriminate between alternative hypothesis, with respect to the information acquisition and learning behaviour of UK households.

Let $\Delta P_{i,t}^{\text{households}}$ be the average perceived house price growth between $t-1$ and t, calculated across all households in district i and year t. I propose the following spatial specification, to characterize the evolution of household beliefs through time:

$$\begin{aligned}\Delta P_{i,t}^{\text{households}} &= \mu_i + \delta_{region,t} + \boldsymbol{\xi} \boldsymbol{C}_{i,t}^{\text{households}} + \rho \Delta P_{i,t-1}^{\text{households}} + \beta_1 \Delta P_{i,t} \\ &\quad + \beta_2 \Delta P_{i,t-1} + \chi V_{i,t} + \beta^* \Delta P_{i,t}^* + \gamma^* \Delta \Pi_{i,t}^* V_{i,t}^* + \lambda^* V_{i,t}^* + \varepsilon_{i,t}.\end{aligned} \tag{2}$$

Here, $\Delta P_{i,t}$ refers to the actually realized house price change, estimated from actually observed transaction-level data, while $V_{i,t}$ is the corresponding housing market turnover in district i in year t.

I control for fixed effects at the district level in order to eliminate any effects of local conditions which are constant through time, and isolate any house price changes which may be purely driven by the aggregate regional market dynamics[10].

I include the set of household-level variables $\boldsymbol{C}_{i,t}^{\text{households}}$ to control for any correlated fundamental economic shocks which may affect neighbouring regions and possibly lead to spurious spatial correlation. I consider the average district-level total household income as a proxy for the level of economic activity and expect it to capture variation in factors which affect the purchasing power of housing market participants (especially on

[10] The identification of local spatial dependence by eliminating the effects of aggregate shocks is in the spirit of Campbell et al. (2011), although my analysis is implemented at a much less granular level.

the demand side). Further, I capture the average households' perceptions of their own financial situation by using survey-based data on financial experiences and expectations over the previous and the next years, respectively. More concretely, I use the answers to a set of categorical questions (listed in the online appendix), to construct dummy variables at district level, which indicate the fraction of households which are in more financially stable situations, more financially vulnerable, optimistic or pessimistic.

The *star* superscript in equation (2) indicates that the respective variables are spatially weighted averages of developments outside district i. In this specification, the coefficient β^* reflects the degree to which perceptions about house price changes in district i are associated with price changes outside district i, controlling for the local price dynamics, and λ^* captures the role of liquidity as an indicator of investor sentiment. A positive and statistically significant coefficient γ^* suggests that the strength of the prices spillover is varying with the level of liquidity in the outside areas.

Analogously to the notation above, let $dispersion_{i,t}^{\text{households}}$ be the *cross-household* standard deviation of perceived house price growth rates. I test the hypothesis that households learn from price development in nearby regions and that a higher level of liquidity is associated with lower cross-sectional disagreement in the following framework:

$$\begin{aligned} dispersion_{i,t}^{\text{households}} &= \alpha_i + \tau_{region,t} + \boldsymbol{\xi} \boldsymbol{C}_{i,t}^{\text{households}} + \kappa \Delta P_{i,t}^{\text{households}} \\ &\quad + \eta_1 \Delta P_{i,t} + \eta_2 \Delta P_{i,t-1} + \varsigma V_{i,t} + \varphi^* \Delta P_{i,t}^* + \zeta^* V_{i,t}^* + u_{i,t}. \end{aligned} \tag{3}$$

Here, the coefficient ζ indicates the strength of the learning mechanism, i.e. the degree to which a wider information set in neighbouring areas leads people to agree more about the estimated likely values of their residential properties, in the eventuality of an immediate sale. In this framework, the main distinction between the two information-based transmission channels (sentiment vs. rational learning) is apparent in the distinction between the coefficients λ^* and ζ^*. If the former is positive and statistically significant, market liquidity can be viewed as an indicator of investor sentiment. In turn, if the latter is negative and statistically significant, it captures the lower uncertainty associated with each individual valuation, and supports the informational role of a more intense trading activity.

2.3 The "ripple effect" revisited

Finally, if market liquidity does play a role in terms of determining the information acquisition of households and leads to cross-district spillovers, a question naturally arising is how the co-movement of turnover relates to the usual spatial dependence of prices widely documented in housing markets. In order to shed light on this question, I estimate a model of house price changes:

$$\Delta P_{i,t} = \eta_i + \tau_t + \varrho \Delta P_{i,t-1} + \lambda V_{i,t-1} + \varrho^* \Delta P^*_{i,t-1} + \lambda^* V^*_{i,t-1} + \nu_{i,t}, \tag{4}$$

where the spatial dependence is captured by the liquidity level in neighbouring regions $V^*_{i,t-1}$,as well as by the weighted average of price changes $\Delta P^*_{i,t-1}$ outside district i.

In this case, λ^* gives the degree to which the liquidity level in neighbouring regions influences local growth rates.

In equation (4), η_i and τ_t are district-level and monthly time period fixed effects, and the estimation procedures are geared towards understanding the effects of neighbouring house prices at local level. However, if spatial spillovers are shown to be prevalent (i.e. if ϱ^* and λ^* are positive and statistically significant), the effects should also materialize at the level of average prices. Indeed, theory predicts that spillovers have the potential to magnify local shocks and lead to increases in average house prices, through feedback effects.

In order to assess any likely net contribution of liquidity spillovers to the dynamics of average house prices, I estimate the following specification:

$$\begin{aligned} \Delta P_{i,t} &= \eta_i + \varrho \Delta P_{i,t-1} + \lambda V_{i,t-1} + \varrho_t^* \Delta P_{i,t-1}^* + \lambda_t^* V_{i,t-1}^* \\ &\quad + \mu_t^* \Delta P_{i,t-1}^* V_{i,t-1}^* + \nu_{i,t}, \end{aligned} \tag{5}$$

with λ_t^* and μ_t^* restricted to be equal to zero. Compared to equation (4), the coefficients ϱ_t^*, λ_t^* and μ_t^* are hereby also allowed to be time-varying. This is essential in order to not restrict the contribution of spillover effects to be driven solely by the aggregate dynamics of turnover and prices. Instead, this specification also allows me to uncover the periods when spillovers are more likely to matter.

I denote the corresponding fitted values obtained after OLS estimation of equation (5) by $\Delta \widehat{P}_{i,t}^A$.

In a second step, the restriction is eliminated and the obtained fitted values are denoted by $\Delta \widehat{P}_{i,t}^B$. The average resulting difference between $\Delta \widehat{P}_{i,t}^B$ and $\Delta \widehat{P}_{i,t}^A$ isolates the net contribution of liquidity spillovers:

$$\Delta \overline{P}_t \equiv \frac{1}{N} \sum_{j \in \mathbb{D}} (\Delta \widehat{P}_{i,t}^B - \Delta \widehat{P}_{i,t}^A), \tag{6}$$

where N is equal to the total number of districts. Importantly, the empirical specification in equation (5) does not contain time period fixed effects, because the interest is in understanding the drivers of the aggregate dynamics of prices.

3 Data

The main dataset comes from the Land Registry and covers completed residential property transactions for the period 1995 to 2013. The data are collected as part of the land registration process and contain the complete set of property transactions at market value that are lodged for registration in England and Wales[11]. The size of the sample is equal to 19,245,940. Each property transaction is characterized by a set of characteristics, the price at which the transaction was settled and the date when the sale was completed, as stated on the transfer deed. The location of individual properties is identified by their postcodes and addressable object names. A detailed overview of the respective fields structure is given in the online appendix.

In the UK, postcodes provide for a very granular geographical location of properties, often covering just one building or segment of a street. I use the UK Postcode Directory to obtain other levels of geographic aggregation. In particular, I implement my empirical analysis at the level of Local Authority Districts (henceforth, I refer to these regions simply as districts). These are subdivisions of local UK government, with a total of 348 districts in England and Wales[12].

The Boundary Dataset of the Office for National Statistics (ONS) allows to capture the spatial dimension of the price and liquidity spillovers. I use the geospatial polygon coordinates to calculate average longitude and latitude measures and derive pairwise distances between districts. Compared with simple contiguity indicators, as employed for example in Pesaran et al. (2011), the distance-based modeling of spatial interactions accounts for the fact that housing market dynamics are inextricably linked with household-level decisions to migrate and to commute, as well as with the degree to which information about house prices is disseminated across different towns and regions - in the spirit of Anselin (1988).

[11] The transaction-level Land Registry data are subject to monthly revisions. All results in this paper are constructed by using the September 2014 release. The data exclude all commercial transactions, sales of part of a property, repossession sales or transfers between parties on divorce, as well as transfers, conveyances, assignments or leases at a premium with nominal rent, vesting deeds transmissions or leasehold transactions for properties with less than seven years remaining on the lease.

[12] The geographical, administrative and denomination structure of the districts has changed in 2001 and 2009. These changes often involve slight reformulations of the district names or mergers of adjacent areas. As far as possible, I am identifying the changes and matching respective variables accordingly. For a sample of between 5 and 10 districts, depending on the variable and data source, definite matches cannot be established. In such cases, I drop the districts from the corresponding sections of the analysis. I use the 2009 codification of district areas throughout.

The exposure of each district to developments outside its geographic borders is determined by the spatial weights $\omega_{ij.}$, where i is the reference district and j indexes the potential source of the spillover. Given that I am interested in unit-free measures of cross-district exposure, the weights are normalized such that:

$$\sum_{j \in \mathbb{D}} \omega_{ij} = 1, \forall i \in \mathbb{D}.$$

Let q_{ij} be the distance between i and j, calculated from geospatial polynomial coordinates. By convention, both q_{ii} and the weights ω_{ii} are imposed to be equal to zero, for all districts i. The weights ω_{ij} are therefore given by the following formulas:

$$\omega_{ij} \equiv \frac{1/q_{ij}}{\sum_{k \in \mathbb{D}} 1/q_{ik}}, \forall i, j \in \mathbb{D}, i \neq j. \text{ and } \omega_{ii} = 0, \forall i \in \mathbb{D}. \tag{7}$$

The conversion of distances in spatial weights is generally a degree of freedom for which little systematic guidance exists. I choose the inverse-distance method in equation (7) following the usual practice in the spatial housing literature. The main economic reason justifying this choice is that it implies a continuous smooth link between regions, as opposed to defining abrupt limit points.

I characterize the cross-district spatial heterogeneity along different structural, social and economic dimensions. First, the degree of home ownership, as well as the composition of the housing stock (i.e. the relative number of flats, terraced, detached or semi-detached houses) are natural determinants of regional variations in density and turnover. Second, the demographic composition of households within an area affects their tenure choices, earnings potential and labour mobility, leading to cross-district variation in the sensitivity of housing demand to income and labour market shocks. Third, the financial situation of households and the fraction of owned residences which are subject to a mortgage contract materially affect the transmission of monetary policy and financial market shocks onto local house prices and turnover. I obtain variables capturing these different dimensions from the Neighbourhood Statistics Dataset. I capture local economic conditions by using two variables: first, labour income from the Survey of Hours and Earnings and second, unemployment claims from the Claimaint Count statistics. All of these different datasets are provided by the Office for National Statistics.

Cross-regional migration patterns are a key determinant of housing market spillovers. However, unlike in most other European countries, there is no compulsory system of residential population registration in the UK. The official census data provides detailed information about population status at a very granular geographic level, but these are only available at two different points in time which are a decade apart (2001 and 2011). Therefore, I draw upon the Internal Migration Estimates (IME) to retrieve the movements of population across districts. The IME database is constructed based on three primary administrative sources (the National Health Service Central Register, the Patient Register Data Service and the reports by the Higher Education Statistics Agency). The data are compiled, validated and released by the ONS[13].

To insure cross-district comparability, I normalize the figures by dividing through the total population of the district:

$$M_{i,t}^{Inflow} \equiv \frac{Inflow_{i,t}}{Population_{i,t-1}} \text{ and } M_{i,t}^{Outflow} \equiv \frac{Outflow_{i,t}}{Population_{i,t-1}},$$

where $Inflow_{i,t}$ and $Outflow_{i,t}$ are the gross population inflows and outflows into and out of area i, respectively.

Figure 1 suggests that both gross inflows and outflows are likely to be associated with increases in housing turnover. Since the main results in terms of the residual

[13]Comparisons with census data indicate that the identified migration patterns across areas are precise, except for males aged between 16 and 29. Since homeownership is low in this age category and the participation in housing transactions very limited, I do not see any cause for concern. The data validation process is described in more detail in ONS (2014).

component of the spatial dependence of turnover are entirely robust to the choice of the measure of district-level migration, and in order to keep the estimation framework reasonably parsimonious, I include only the average between inflows and outflows in the benchmark panel specification:

$$M_{i,t} \equiv \frac{Inflow_{i,t} + Outflow_{i,t}}{2 \cdot Population_{i,t-1}}.$$

The household-level data on perceptions about house price growth are from the British Household Panel Survey (BHPS) and cover the years 1995 to 2008. The BHPS is an annual panel survey of approximately 5,500 households in Britain. Individual respondents are surveyed starting with the point at which they form households with one the members of the original survey wave in 1991. The sample I use corresponds to the households which are present in the BHPS and live in the same house for two consecutive years. In the online appendix, I show that the average perceived house price growth rate is a very close approximation of the actually observed price dynamics at district level.

In the next section, I describe how I use the dataset assembled by merging the observations and area characteristics from these various sources in order to shed light on the issue of spatial liquidity spillovers and their impact on property prices.

4 Results

4.1 Housing turnover and population migration

Figure 1 illustrates the cross-sectional relationship between housing turnover and individual mobility. First, I normalize the migration statistics by dividing through the total population of the district. I then calculate simple averages over the entire time period and obtain a single measure of population mobility per district. Finally, I plot average gross population inflows and outflows against average yearly turnover values, as shown in Panels A and B. A positive relationship between flows and turnover is, of course, to be expected: relatively high numbers of residential property transactions are more likely to be observed in areas in which the population is more mobile - the cross-sectional correlation coefficient between average population inflows and turnover is equal to 0.38.

Analogously, higher outflows are also associated with increased turnover, albeit the strength of the relationship is much weaker - the correlation coefficient is equal to 0.16. I do not observe the migration motives of individuals, but a clear pattern emerges, which may be informative in this regard. On one side, for moderate levels of mobility, the relationship with local housing market turnover is strongly positive. In these areas, the cross-regional spillovers in market liquidity are likely to be attributable to the effect of migration. To the contrary, in districts which experience either very large inflows or outflows, the relationship vanishes, likely because migrants are moving into the renting sector or because they leave from shared accommodation, such as young adults moving away from university towns or departing their parents' homes.

In Panel C, I calculate average net relative changes in the population of the districts and document a substantial cross-sectional association with average housing market turnover - the correlation coefficient is equal to 0.50. Areas which experienced net population inflows over the period between 1995 and 2013 tend to also have more active housing markets.

In Table 1, I describe the degree to which the regional variation in liquidity is associated with heterogeneity across a set of other social, economic and demographic characteristics. The four columns report means of the respective variables, for different sub-samples of the set of districts, sorted according to the yearly turnover.

In the bottom quartile, the average transaction volume per year (during the period 1995 to 2013) is found to be equal to 1.50% of the total housing stock, while in the top quartile, the average yearly turnover is 2.20%. In illiquid areas, the homeownership rate seems to be lower, which is consistent with the intuition that rented properties trade less often than owner-occupied ones. At the same time, mortgage indebtedness is higher in more liquid areas, the fraction of single-person households and the unemployment rate are lower and the fraction of people with higher education degrees is higher. Overall, this pattern is entirely consistent with the broad positive association between higher turnover and higher labour mobility.

Finally, confirming the link between liquidity and price dynamics which is usually prevalent in financial markets, the last row of the table indicates that the standard deviation of house price growth is monotonically decreasing, as turnover increases. In districts which are generally characterized by low liquidity levels, prices are thus also more volatile.

4.2 Spatial dependence in housing turnover

Table 2 collects the benchmark results. In the first row, I report the estimated autoregressive coefficient of district-level turnover. Across the three estimation variants, it varies between 0.45 and 0.46. This relatively low level of persistence is important because it alleviates any concern about the possible spurious nature of the spatial relationships.

In a specification which includes both district-level and time period fixed effects, which I report in the third column, I find that a one standard deviation increase in turnover in nearby regions is associated with a 0.80 standard deviations higher local turnover during the next month. Importantly, this effect is net of the role of local migration patterns. Migration also contributes to the dynamics of turnover in a statistically significant way, but the effect is rather modest. A one standard deviation higher mobility is associated with 0.20 standard deviations higher turnover.

Concerning the behavioural effects discussed above, which generate positive feedback from prices to liquidity and which occur e.g. in the context of the loss aversion hypothesis emphasized by Genesove and Mayer (2001), I find a statistically significant coefficient on lagged house price growth only in a specification which excludes time fixed effects. I therefore conclude that such positive feedback is restricted to the aggregate component of house prices (and price expectations) and it vanishes entirely at the local level. Interestingly, the spatial effect of prices on local liquidity is estimated to be indistinguishable from zero, which eliminates the possibility that the regression may be affected by the correlation between regional turnover and housing returns.

4.3 Household-level sentiment and learning

Table 3 reports estimation results referring to the evolution of household-level perceptions about house price growth. In the first column of Panel A, the estimated model is a simple AR(1) As discussed by Glaeser et al. (2014), house price growth rates are serially correlated and this seems to be also reflected in the household perceptions. Interestingly, once I control for the actual price changes within the district (calculated with transaction-level data from the Land Registry), the time dependence vanishes. This indicates that household perceptions do not deviate persistently from actually realized prices.

In the online appendix, I show that average perceptions tended to move in lockstep with actual market-wide developments over the last decades. This provides an essential validation of the quality of responses in the BHPS. At the same time, it reinforces the idea that households possess substantial information about the value of their properties, despite the inherent thinness of the market and the fact that most properties are not subject to transactions over relatively long periods of time.

In the second column, I report a strong positive co-movement between perceptions and local housing turnover. However, this co-movement vanishes completely (as reported in the third column), when controlling for price developments in neighbouring regions. This suggests a prominent role for price spillovers in this market - as opposed to alternative behavioural or sentiment-based explanations.

The only role for liquidity seems to be as a means to increase the degree to which higher prices in neighbouring areas affect the local perceptions about house price growth. This is consistent with a rational learning mechanism, in which households place greater trust in the signals obtained from observing market developments, the higher the number of transactions - and thus, the higher the number of different signals.

Finally, the estimation results collected in the last two columns suggest that the liquidity dynamics in neighbouring districts does not materially influence the perceptions of households, once we include time fixed effects and eliminate the average market-wide components. I see this as evidence against a separate role for liquidity as an indicator of investor sentiment.

Instead, the last row of Table 4 shows that higher liquidity in neighbouring districts seems to be strongly negatively associated with the cross-household disagreement in terms of perceived house price growth rates. This finding is consistent with a rational learning mechanism, especially since the residual effect of outside liquidity on *average* perceptions is estimated to be negative (albeit very imprecisely estimated, as reported in the last column).

The result that perceptions are more dispersed when they are rising on average (illustrated in the first row of Panel A in Table 4) may be suggestive of behavioural effects. Some households possibly stick more to their purchase price, while others are generally seeking the opportunity to hold more optimistic beliefs. Whenever the average level of perceptions rises, this leads to a positive association with disagreement.

In Panel B of Table 3, I report estimated coefficients which characterize the relationship between perceptions of house price growth and other household-level variables. I find no statistically significant effect of the income growth rate. This is reinforcing evidence for the fact that controlling for actual price developments eliminates any relevant potentially spatially correlated variation in district-level fundamentals.

Interestingly, I find strong effects linking general pessimism about financial matters with negative perceptions about house values - while no such relationship is evident on the positive side. This asymmetry is potentially magnifying the widely documented disposition effect of households and illustrating the fact that illiquidity spirals can be extremely damaging particularly in downside markets, when negative economic developments affect the perceptions of households about the value of their own house, leading to fewer sales, higher time-on-market and substantial price decreases.

4.4 Cross-sectional variation in market turnover

If households use the available set of transactions in neighbouring areas in order to learn about the values of their own properties, as is suggested by the household-level empirical evidence described above, this has important implications for the cross-sectional variation of market turnover across districts. The intuition hereby is that market developments accompanied by a higher number of transactions are better signals of underlying home values than those occurring in a more informationally poor environment. Therefore, when liquidity is high, the information sets of households tend to be better aligned and the changes in turnover become more homogenous across the nation.

The recent boom-bust patterns in the UK housing market are an adequate illustration of this phenomenon. The market experienced unusual levels of market activity during the period prior to 2007, which were associated with strong co-movement patterns across districts and regions. As liquidity started to dry up during the first months of the burgeoning financial crisis at the end of 2007, market developments became much more heterogeneous and substantial cross-regional differences became apparent.

Table 5 reports the results from cross-sectional regressions of changes in market turnover during two distinct time periods: 2005 to 2007 and 2007 to 2009, respectively.

In a first step, my interest lies in the degree to which turnover may be asymmetrically distributed across areas with generally higher or lower levels of liquidity. I find that in the pre-crisis period, the explanatory power of market liquidity is virtually zero. This suggests that the boom phase of the housing cycle, characterized by overall high liquidity levels, can be seen as largely synchronous across regions and districts. To the contrary, when turning to the post-crisis period, I find that cross-district variation in market liquidity alone can explain 18% of the observed variation of turnover. In fact, the estimated coefficient capturing this relationship is highly statistically significant and economically large in magnitude. In a district which lies one standard deviation above the mean in terms of its average liquidity, turnover grows by 3.8 percent more between 2007 and 2009. This corresponds to about one half of the realized standard deviation within the period.

In a second step, I consider a set of additional district-level variables, which capture the income, education, financial indebtedness, structural composition and economic situation of households in specific areas. Again, as reported in the second column, the adjusted R^2 of the regression remains below a value of 0.01 for the pre-crisis period. This confirms the substantial co-movement patterns in the boom phase and is consistent with the observation that during periods of high liquidity cross-district learning is more intense, as described in the previous section.

As concerns the bust phase, the picture is very different. The last column shows that the expanded set of district-level variables explains 58% of the variation in turnover, lending credibility to the hypothesis that during times of lower liquidity local conditions determine housing market outcomes to a much higher degree. The estimated coefficients are generally consistent with the view that the crisis has affected mostly highly indebted households, as well as those which live in poorer areas, where unemployment rates are higher and a higher fraction of properties are financed through mortgage contracts. Importantly, the liquidity of the local market remains a significant determinant of the cross-district distribution of post-crisis changes in turnover. In more liquid areas, the crisis seems to have had a more benign effect[14], consistent with the hypothesis that liquidity had been unsustainably high during the pre-crisis period especially in areas which were historically more illiquid.

4.5 The "ripple effect" revisited

Table 6 revisits and confirms the positive co-movement between turnover and house price growth, as well as the spatial dependence of house prices, in my sample of districts in England and Wales, analyzed for the period between 1995 and 2013. The first two columns indicate a positive and statistically significant effect of past liquidity on current price changes, very likely an outcome of upwards revisions of reservation prices by sellers, following the higher probability of a successful transaction. Analogously, the spatial dependence parameter is estimated to be equal to 0.71 and is found to be highly statistically significant.

In the third column, I consider the role of liquidity in neighbouring areas. Interestingly, the magnitudes of both the co-movement and the price effects are greatly

[14] These effects are robust to the exclusion of certain regions like e.g. London, in which house prices during the post-crisis period are also driven by the increases in foreign demand for real estate as a safe haven asset.

reduced. To the contrary, liquidity in neighbouring regions seems to have a high explanatory power for local house price changes. Given that this specification also includes time period fixed effects, the spillovers are identified by pure cross-sectional variation in regional liquidity levels. This suggests that the so-called "ripple" effect[15], which has been widely documented and validated across countries and time periods, has a substantial liquidity component.

4.6 Dynamics of average house prices

In Figure 2, I attempt to quantify the net contribution of spatial liquidity spillovers to the overall dynamics of house prices. First, I estimate a simple spatial autoregressive model of district-level price changes in which I restrict all spatial effects of liquidity to be equal to zero. I then allow it to determine the growth rates in house prices explicitly and compare the average fitted values to ones obtained in the restricted case. The green shaded bars in Figure 2 capture the magnitude of the net contribution of spillovers. The largest effects occur around the start of the mortgage-induced boom years in 2002 and 2003, as well as during the pronounced market downturn of 2007 and 2008.

The distinguishing feature of this exercise is the large number of degrees of freedom embedded in the specification. All coefficients which characterize the spatial dynamics are allowed to vary through time. This insures that the time path of the differential effects I measure are not driven by the dynamics of aggregate turnover, but instead reflect the dynamic state-contingent nature of the spatial relationships.

[15] In the urban economics literature, the term "ripple effect" has become a common way to refer to the dynamic spatial dependence of house prices, for example in Holly et al. (2010) and Pesaran et al. (2011).

5 Conclusion

The spatial correlation across neighbouring markets and the positive relationship between liquidity and price growth are two widely-held tenets of housing market research during the last decades. I use a dynamic model of spatial dependence in order to highlight a dimension which has been missed by empirical and theoretical research so far: the possibility that information is transmitted across regions through co-movements in market liquidity.

The results strongly indicate that housing market liquidity has an important spatial component, which cannot be explained fully by cross-regional population flows. I also find that there is no residual role for liquidity as a determinant of investor sentiment. Instead, I report suggestive evidence that households are rationally learning from price developments in neighbouring areas.

A question naturally arising in this context is to what degree the effects I uncover are manifestations of the spatial diffusion of local shocks, affecting aggregate housing market prices and liquidity. These transmission mechanisms are essential for policy makers, in their attempt at insuring the stability of the financial system and the wide affordability of housing. Despite the strict rationality of the household-level learning mechanisms, the diffusion of shocks across regions may possibly lead to feedback and acceleration effects.

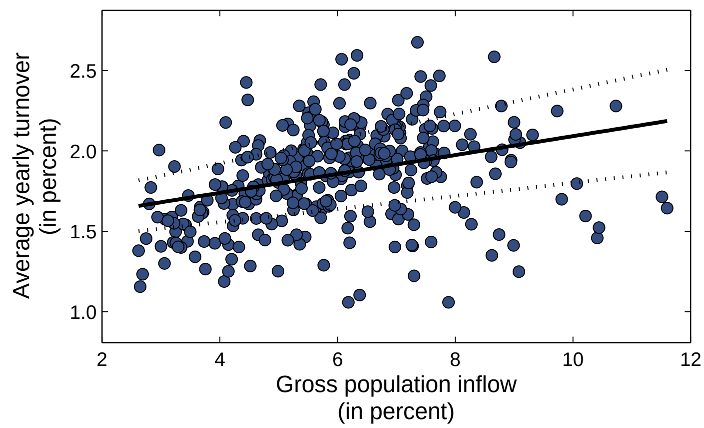
At the same time, a better understanding of the cross-regional patterns of price growth and liquidity is important for investors in residential real estate. Especially in a market with thinly traded assets, with significant limits to arbitrage and locally clustered dynamics, liquidity premia are non-negligible and the returns to market timing can be substantial.

Figure 1

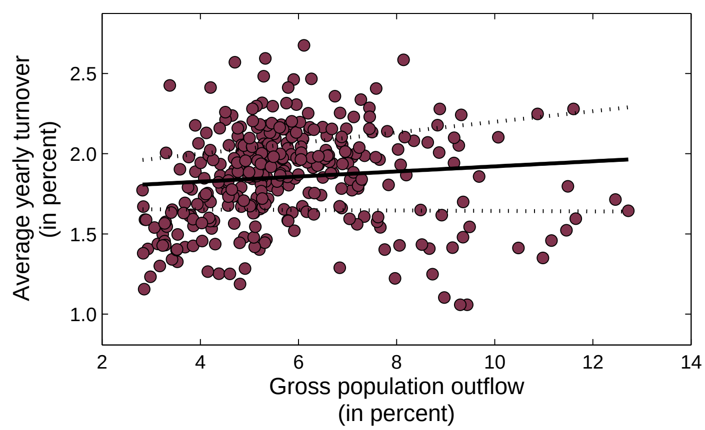
Local liquidity and population mobility

The figure reports the cross-sectional relationship between housing market turnover and migration. For each district, I calculate the average yearly turnover and the average population inflows and outflows. The latter are given as a share of the total population of the district in 2001. The dark line plots fitted values from simple univariate regressions between respective variables and the dotted lines indicate 95% confidence intervals.

Panel A



Panel B



Panel C

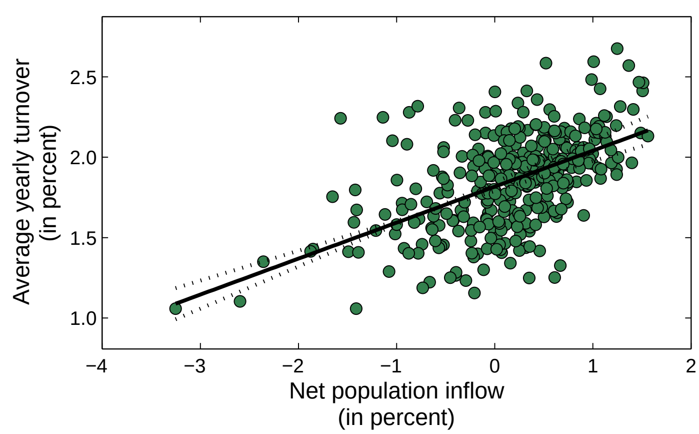


Figure 2

Residential house price dynamics: The role of liquidity spillovers

The figure reports the contribution of liquidity spillovers to the average yearly changes in the prices for residential real estate. I estimate two versions of spatial regressions of the form:

$$\Delta P_{i,t} = \eta_i + \varrho \Delta P_{i,t-1} + \lambda V_{i,t-1} + \varrho_t^* \Delta P_{i,t-1}^* + \lambda_t^* V_{i,t-1}^* + \mu_t^* \Delta P_{i,t-1}^* V_{i,t-1}^* + \nu_{i,t},$$

where $\Delta P_{i,t}$ is the change in house prices in area i in period t, $V_{i,t}$ is the local housing turnover, and $\Delta P_{i,t}^*$ and $V_{i,t}^*$ are the spatially weighted house price changes and turnovers, respectively, calculated for areas outside i. In the first step, the coefficients λ_t^* and μ_t^* are restricted to be equal to zero. The corresponding obtained fitted values are denoted by $\Delta \widehat{P}_{i,t}^A$. In the second step, all coefficients are unrestricted and the obtained fitted values are denoted by $\Delta \widehat{P}_{i,t}^B$. The gray areas report yearly averages of the fitted values $\Delta \widehat{P}_{i,t}^A$ and the green areas report the differences $\Delta \widehat{P}_{i,t}^B - \Delta \widehat{P}_{i,t}^A$, adjusted such that the overall reported magnitudes are interpretable as yearly price changes.

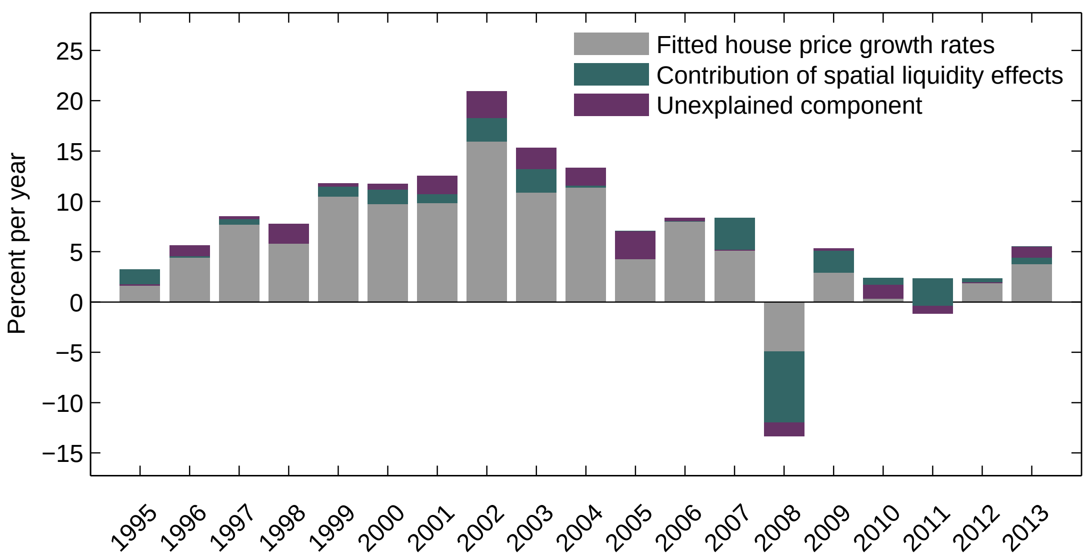


Table 1

Local liquidity and spatial heterogeneity

The table illustrates the relationship between the yearly housing turnover and selected district-level variables. I report average values, calculated for each of four quartiles of the distribution of yearly turnover. The fraction of people who own their main residence is given as a share of the total number of households registered as residing in the district. The fraction of owned residences which are held with a mortgage is calculated in reference to the total number of households which own their main residence. For the reported share of flats, the reference level is the total housing stock. The calculation base for the unemployment rate and the fraction of people with higher education degrees is the total number of persons aged 16 or older. The local migration numbers refer to a yearly frequency and are normalized by the total number of people in the district. All demographic and social variables are obtained from the 2001 wave of the census, as reported by the Office for National Statistics. The migration variables are calculated and reported by the Local Migration Unit and cover the period 1999 to 2013.

		Quartiles of the cross-sectional distribution of turnover			
		1^{st}	2^{nd}	3^{rd}	4^{th}
Average turnover	*(percent per year)*	1.47	1.78	1.97	2.22
Fraction of households which own their main residence	*(percent)*	59.68	67.32	69.57	68.60
Fraction of owned residences which are held with a mortgage	*(percent)*	30.56	34.41	35.04	33.93
Number of flats, as a fraction of total properties	*(percent)*	17.40	16.61	10.30	14.00
Fraction of single-person households	*(percent)*	18.34	16.60	15.61	16.57
Average unemployment rate	*(percent)*	5.50	4.27	3.63	3.62
Fraction of people with higher education degrees	*(percent)*	11.93	12.32	12.32	12.34
Inflow of people, as a share of total population	*(percent per year)*	5.29	5.81	6.37	6.87
Outflow of people, as a share of total population	*(percent per year)*	5.65	5.63	5.96	6.25
Standard deviation of house price growth	*(percent per year)*	5.50	5.45	5.16	5.09

Table 2

Spatial dependence of housing market liquidity

The table reports estimated coefficients from spatial regressions of the form:

$$V_{i,t} = \mu_i + \delta_t + \rho V_{i,t-1} + \rho^* V^*_{i,t-1} + \gamma \Delta P_{i,t-1} + \gamma^* \Delta P^*_{i,t-1} + \varphi M_{i,t} + \boldsymbol{\zeta} \mathbf{F}_{i,t-1} + \varepsilon_{i,t},$$

where $V_{i,t}$ is the housing turnover in area i in period t, $V^*_{i,t}$ is the spatially weighted turnover in areas outside i, $\Delta P_{i,t}$ is the change in local prices and $M_{i,t}$ is the average migration flow in area i. Driscoll-Kraay standard errors with 12 lags are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

		(1)	(2)	(3)
Lagged turnover	ρ	0.45***	0.46***	0.45***
		(0.02)	(0.02)	(0.03)
Spatial dependence	ρ^*	0.55***	0.79***	0.80***
		(0.04)	(0.10)	(0.12)
Local effect of prices	γ	0.26**	0.08	0.06
		(0.10)	(0.05)	(0.06)
Spatial effect of prices	γ^*		-0.48	-0.44
			(0.88)	(0.90)
Local effect of migration	φ			0.20***
				(0.04)
Unemployment claims	ζ_1	-0.21*	-0.15***	-0.18***
		(0.11)	(0.03)	(0.03)
Income growth	ζ_2	0.37**	0.04	0.04
		(0.16)	(0.04)	(0.04)
District-level fixed effects		Yes	Yes	Yes
Time fixed effects		No	Yes	Yes

Table 3
Residential property valuations by households

The table reports estimated coefficients from spatial regressions of the form:

$$\begin{aligned}\Delta P_{i,t}^{\text{households}} &= \mu_i + \delta_{region,t} + \boldsymbol{\xi} \boldsymbol{C}_{i,t}^{\text{households}} + \rho \Delta P_{i,t-1}^{\text{households}} + \beta_1 \Delta P_{i,t} + \\ &\quad \beta_2 \Delta P_{i,t-1} + \chi V_{i,t} + \beta^* \Delta P_{i,t}^* + \gamma^* \Delta P_{i,t}^* V_{i,t}^* + \lambda^* V_{i,t}^* + \varepsilon_{i,t},\end{aligned}$$

where $\Delta P_{i,t}^{\text{households}}$ is the average perceived house price growth between $t-1$ and t, calculated across all surveyed households in district i and year t. $\Delta P_{i,t}$ refers to the actually realized house price change, estimated from Land Registry data. $V_{i,t}$ is housing market turnover in district i in year t. The set of household-level controls $\boldsymbol{C}_{i,t}^{\text{households}}$ captures the average income dynamics within a district, as well as average perceptions of households about their financial situation. The star superscript indicates that the variables are spatially weighted averages of developments outside district i. In Panel A, I report the coefficients which characterize housing-market variables. In Panel B, I report estimated coefficients which capture the role of perceptions and income dynamics at household level, corresponding to the specification in column (5) of Panel A. Driscoll-Kraay standard errors with 12 lags are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

Panel A
Spatial dependence

		(1)	(2)	(3)	(4)	(5)
Household perceptions	$\Delta P_{i,t-1}^{\text{households}}$	0.44***	0.00	-0.01	-0.16***	-0.16***
		(0.07)	(0.05)	(0.03)	(0.03)	(0.03)
Actual price changes	$\Delta P_{i,t}$		0.52***	0.23***	0.12***	0.12***
			(0.06)	(0.04)	(0.03)	(0.03)
Lagged price changes	$\Delta P_{i,t-1}$		0.38***	0.25***	0.13***	0.13***
			(0.03)	(0.03)	(0.03)	(0.03)
Local turnover	$V_{i,t}$		2.06***	-0.81*	0.06	0.17
			(0.73)	(0.44)	(0.42)	(0.37)
Price spillovers	$\Delta P_{i,t}^*$			0.65***	0.82**	0.88**
				(0.05)	(0.37)	(0.37)
Acceleration effects	$\Delta P_{i,t}^* V_{i,t}^*$			0.39***	0.09	0.41
				(0.06)	(0.33)	(0.38)
Liquidity as sentiment	$V_{i,t}^*$					-5.67
						(4.14)
District-level fixed effects		Yes	Yes	Yes	Yes	Yes
Region x time fixed effects		No	No	No	Yes	Yes
Household-level controls		No	No	No	No	Yes

Table 3

Residential property valuations by households

(continued)

Panel B

$\boldsymbol{\xi}$ coefficients on household-level variables

Negative financial situation	-10.35***
	(3.68)
Positive financial situation	-0.03
	(1.31)
Expected worsening of financial situation	-5.64**
	(2.69)
Expected improvement of financial situation	2.06
	(1.88)
Average income growth rate	-0.12
	(0.24)
District-level fixed effects	Yes
Region x time fixed effects	Yes

Table 4

Cross-sectional variation of household perceptions

The table reports estimated coefficients from a spatial regression of the form:

$$\begin{aligned} dispersion_{i,t}^{\text{households}} &= \alpha_i + \tau_{region,t} + \boldsymbol{\xi} \boldsymbol{C}_{i,t}^{\text{households}} + \kappa \Delta P_{i,t}^{\text{households}} + \eta_1 \Delta P_{i,t} \\ &\quad + \eta_2 \Delta P_{i,t-1} + \varsigma V_{i,t} + \varphi^* \Delta P_{i,t}^* + \zeta^* V_{i,t}^* + u_{i,t}, \end{aligned}$$

where $dispersion_{i,t}^{\text{households}}$ is the standard deviation of perceived house price growth between $t-1$ and t, calculated across all surveyed households in district i and year t. $\Delta P_{i,t}^{\text{households}}$ is the corresponding average perceived house price growth. $V_{i,t}$ is housing market turnover in district i in year t. The set of household-level controls $\boldsymbol{C}_{i,t}^{\text{households}}$ captures the average income dynamics within a district, as well as average perceptions of households about their financial situation. The star superscript indicates that the variables are spatially weighted averages of developments outside district i. Driscoll-Kraay standard errors with 12 lags are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

Household perceptions	$\Delta P_{i,t}^{\text{households}}$	0.66***
		(0.06)
Actual price changes	$\Delta P_{i,t}$	0.01
		(0.03)
Lagged price changes	$\Delta P_{i,t-1}$	-0.02
		(0.02)
Local turnover	$V_{i,t}$	0.06
		(0.40)
Price spillovers	$\Delta P_{i,t}^*$	-0.08
		(0.16)
Cross-ward learning	$V_{i,t}^*$	-7.06**
		(3.05)
District-level fixed effects		Yes
Region x time fixed effects		Yes
Household-level controls		Yes

Table 5

Explaining the cross-sectional variation

The table reports estimated coefficients from a cross-sectional regression of the form:

$$\Delta V_{i,period} = \upsilon_i + \eta \overline{V}_i^{<2005} + \sum_{k=1}^{K} \beta_k X_{i,k} + \varepsilon_i,$$

where $\Delta V_{i,period}$ is the total change in turnover during two distinct periods: 2005 to 2007 and 2007 to 2009, respectively. $\{X_{i,k}\}_{k=1,...,K}$ are district-level variables, obtained from 2001 Census data. $\overline{V}_i^{<2005}$ is the average turnover level in district i calculated for the period before 2005. Heteroskedasticity-robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

	Pre-crisis changes *- in percent -* (2005 to 2007)		Post-crisis changes *- in percent -* (2007 to 2009)	
	(1)	(2)	(1)	(2)
Average turnover prior to 2005	-0.72	-1.32*	3.79***	0.92**
	(0.58)	(0.79)	(0.43)	(0.43)
Average wage income of resident population		-0.31		1.16**
		(0.87)		(0.52)
People with higher education degrees		-0.82		0.90***
		(0.70)		(0.31)
Properties which are held with a mortgage		0.94		-5.91***
		(0.92)		(0.43)
Number of flats, as a fraction of total properties		0.28		-2.23***
		(1.06)		(0.62)
Average unemployment rate		-0.82		-6.85***
		(0.74)		(0.46)
Adj. R^2 ($\times$ 100)	0.21	0.64	17.80	57.95

Table 6
House price dynamics

The table reports estimated coefficients from regressions of the form:

$$\Delta P_{i,t} = \eta_i + \tau_t + \varrho \Delta P_{i,t-1} + \lambda V_{i,t-1} + \varrho^* \Delta P^*_{i,t-1} + \lambda^* V^*_{i,t-1} + \nu_{i,t},$$

where $\Delta P_{i,t}$ is the change in house prices in area i in period t, $V_{i,t}$ is the local housing turnover, and $\Delta P^*_{i,t}$ and $V^*_{i,t}$ are the spatially weighted house price changes and turnover, respectively, calculated for areas outside i. Driscoll-Kraay standard errors with 12 lags are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

		(1)	(2)	(3)
Effect of local turnover	λ	0.56***	0.25***	0.08**
		(0.10)	(0.05)	(0.04)
Spatial price spillover effect	ϱ^*		0.71***	0.13
			(0.06)	(0.08)
Spatial liquidity spillover effect	λ^*			2.43***
				(0.68)
District fixed effects		Yes	Yes	Yes
Time fixed effects		No	No	Yes

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Theoretical Appendix

Model setup

In this appendix, I illustrate a particular way in which rational learning from prices can lead to spatial dependence of liquidity across otherwise separate housing markets. This serves as a motivation for my analysis of cross-district spillovers in the main body of the paper.

Following Cespa and Foucault (2014), consider a two-period setup, with a representative set of divisible properties trading in the first period in region $i \in \mathbb{I}$ with price p_i[16]. The price p_i is to be determined in equilibrium. The uncertain flow of housing services v_i, which accrues in the second period, is the sum of a spatially correlated stochastic process δ and an idiosyncratic local stochastic component η. The matrix characterizing the cross-district contemporaneous correlation between fundamentals in different areas is denoted by $\Omega = \{\omega^i_j | i, j \in \mathbb{I}\}$:

$$\nu_i = \delta_i + \sum_{j \in I, j \neq i} \omega^j_i \delta_j + \eta_i.$$

Agents in region i perfectly observe δ_i, but they do not observe $\{\delta_j\}_{j \in I, j \neq i}$. As part of their signal extraction problem, they form expectations about the future payoff:

$$E[v_i | \delta_i, \{p_j\}_{j \in I}].$$

The price p_j is not perfectly informative for δ_j because the housing demand in region i has two components: on one side, a quantity u_i from a set of price-inelastic (uninformed, liquidity) traders, and a quantity x_i from a set of risk-averse (informed)

[16] This is a sylized version of a model of the housing market. The maintained assumption is that housing services are perfeclty divisible.

traders, which solve an optimal consumption problem, with CARA utility and risk tolerance γ:

$$\begin{aligned} x_i &= \arg\max_{\widetilde{x}_i} E\left[-e^{-\frac{(\nu_i-p_i)\widetilde{x}_i}{\gamma_i}}|\delta_i, \{p_j\}_{j\in I}\right] \\ &= \gamma_i \frac{E[v_i|\delta_i, \{p_j\}_{j\in I}] - p_i}{Var[v_i|\delta_i, \{p_j\}_{j\in I}]} \end{aligned}$$

The market clearing condition implies that:

$$x_i + u_i = 0.$$

Equilibrium

Following Cespa and Foucault (2014), it can be shown that this model has a rational expectations equilibrium which allows for a linear expression of prices in terms of fundamental shocks:

$$p_i = R_i\delta_i + \sum_{j\in I, j\neq i} (H_i^j \delta_j + C_i^j u_j) + B_i u_i,$$

where the coefficients $\{R_i, H_i^j, C_i^j, B_i\}$ are determined by the following set of non-linear equations:

$$R_i = 1, \tag{8}$$

$$H_i^j = \frac{\omega_i^j \sigma_{\delta_j}^2}{\sigma_{\delta_j}^2 + B_j^2 \sigma_{u_j}^2}, \tag{9}$$

$$C_i^j = H_i^j B_j, \tag{10}$$

$$B_i = \frac{1}{\gamma_i}\left[\sigma_{\eta_i}^2 + \sum_{j\in I, j\neq i} \frac{(\omega_i^j)^2 \sigma_{\delta_j}^2 B_j^2 \sigma_{u_j}^2}{\sigma_{\delta_j}^2 + B_j^2 \sigma_{u_j}^2}\right], \forall i \in I. \tag{11}$$

Co-movement of liquidity

In this framework, liquidity is conceptualized by the inverse of the coefficient B_i, which gives the price impact of a liquidity shock u_i. B_i is therefore a measure of *illiquidity* in region i. From equation (11), it is apparent that a liquidity increase in region j spills over onto region i:

$$\frac{\partial B_i}{\partial B_j} = \frac{(\omega_i^j)^2}{\gamma_i} \frac{\sigma_{\delta_j}^2}{(\sigma_{\delta_j}^2 + B_j^2 \sigma_{u_j}^2)^2} \geq 0.$$

The spillovers are strongest when the price is a more precise signal of fundamentals. i.e. when the reference regions are not only economically important, but also more liquid, as well as during more liquid time periods. Through this learning mechanism, local shocks are transmitted across regions and as a consequence, both prices and liquidity appear to co-move. Moreover, the spillovers can lead prices to deviate from fundamental values (on out-of-equilibrium paths), which is a phenomenon observationally equivalent to the "market sentiment" of Baker and Wurgler, but arising as an outcome of rational learning.

Example: Calibration

In order to analyze the implications of the model in terms of the effects of shocks on regional liquidity, consider the following calibration of the deep parameters:

- $\sigma_{\delta_j} = 1, \forall j$.
- $\gamma_j = 0.75, \forall j$. ($\gamma_1$ changes to 0.85 in alternative scenarios)
- $\sigma_{u_j} = 0.5, \forall j$.
- $\sigma_{\eta_j} = 0.5, \forall j$.

Feedback effects

Consider an exogenous increase in the risk tolerance γ_i in region i. This implies higher liquidity (lower illiquidity B_i) in region i itself:

$$\frac{dB_i}{d\gamma_i} < 0$$

However, if $\omega_i^j > 0$, i.e. if there are common shocks affecting housing markets contemporaneously, a liquidity feedback loop arises. Consider the following example, where I present two different network structures of the housing market, for the stylized case of three regional housing markets:

Case 1	**Case 2**
Segmented markets	Complete network structure
$\Omega = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$	$\Omega = \frac{1}{3}\begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$
$\Delta B_i = -0.49$	$\Delta B_i = -1.32$

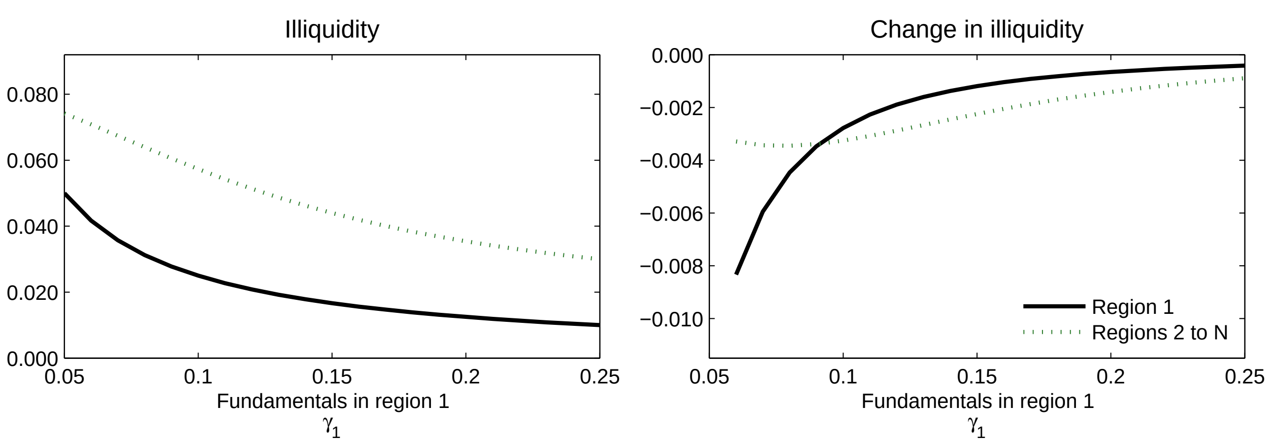
In the first case (segmented markets), all regions are isolated from each other. In this case, the effect of an increase of γ_i from 0.75 to 0.85 leads to a decrease in illiquidity (i.e. an increase in liquidity) equal to 0.49. The same exogenous shock decreases region-i illiquidity by more than double, in the case in which the network structure is complete, i.e. shocks affect all regions simultaneously.

Asymmetric effects

Let N be the number of regions, where - without loss of generality - the first region ($i = 1$) is a dominant one (e.g. London in the United Kingdom). In this framework, shocks which affect the dominant region also affect the rest of the country, but local shocks do not affect the dominant region:

$$\Omega = \frac{1}{2} \begin{pmatrix} 2 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & \cdots & 1 \end{pmatrix}_{N \times N}$$

In the figure below, I report the comparative statics of equilibrium liquidity across regions, for different levels of fundamentals in the dominant region[17]. The results show how, in this model, liquidity levels are spatially related, and - for high levels of illiquidity - the responses outside region 1 can be even more pronounced than in region 1 itself. Absent the learning mechanism described above, regions 2 to N would be isolated from changes in γ_1, so any changes in illiquidity captured by the dotted line are entirely driven by cross-regional learning from observed prices.



[17]In this setup, the only fundamental quantity affecting equilibrium outcomes is the region-specific risk tolerance level γ.

Online Appendix to

Understanding Housing Market Spillovers: Migration, Sentiment and Information Acquisition

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Appendix A

Spatial heterogeneity and changes in housing demand

If agents use the observed transactions in neighbouring areas to learn about changes in underlying home values, an immediate question is to what degree these effects affect the aggregate dynamics of the UK housing market. I am especially interested in the question of whether households are able to distinguish between different types of shocks, i.e. whether spillovers arise independently of the likely source of variation in the housing demand of neighbouring areas.

The UK housing market has experienced two prominent market upswings during the last decade. First, a mortgage-induced boom between 2001 and 2006, driven by a relaxation of the borrowing conditions of households. Second, a substantial increase in house prices in London and the South-East region, driven by the role of UK real estate as a safe haven asset for global capital.

Have these two episodes been characterized by spatial liquidity spillovers and the type of phenomena mentioned above? Were households able to distinguish the temporary and localized nature of increased foreign demand? To answer this question, I exploit the spatial heterogeneity in the degree to which changes in financial conditions and the higher demand by foreign investors have affected the liquidity of local markets, through a two-stage difference-in-difference estimation strategy.

The first identifying assumption is that shocks to the cost of mortgage borrowing are likely to have a larger effect on areas where the degree of indebtedness is higher. This holds naturally in a context in which young agents become better able to overcome binding borrowing constraints or if life-time resources of existing owners are higher due the decreases in mortgage servicing costs and they can more easily allocate the necessary downpayment amounts in order to move into a more desirable property[18].

[18] At the same time, this assumption can be justified if changes in credit market conditions do not immediately affect the portfolio choice (real vs. financial assets) of households which own their

Since the share of mortgage borrowers varies considerably across districts, I am identifying the effect of financial conditions by observing the differential impact of the changes in interest rates on areas in which mortgage borrowing is more pervasive, relative to areas in which outright purchases are the norm. Similar approaches of using regional house price heterogeneity to identify fundamental drivers of housing markets have recently been implemented at zip code level in the US by Adelino et al. (2012) and Favara and Giannetti (2014).

Formally, let $f_i^{mortgage}$ denote the fraction of properties in district i which are subject to a mortgage contract and r_t the average economy-wide mortgage borrowing rate in period t. I therefore project $V_{i,t}$, the turnover in district i and period t, on the interaction term $f_i^{mortgage} r_t$, to obtain the fitted values $\widehat{V}_{i,t}$, which will be used below.

The second identifying assumption stems from Badarinza and Ramadorai (2014), where we link particular areas of London with international political developments, to show that in response to unusually high levels of political risk in foreign countries, housing market activity intensifies in areas of the city which have a higher share of the population born in those countries. I therefore project $V_{i,t}$ on a set of interaction terms between $f_{i,k}^{w}$, the shares of people born in country k, and $z_{t,k}$ the (lagged) levels of political risk in country k.

I use the fitted values from each of these projection exercises $\widehat{V}_{i,t}$ to calculate the spatial lag variable $\widehat{V}_{i,t}^{*}$, and repeat the estimation of the benchmark model, with:

$$V_{i,t} = \mu_i + \delta_t + \rho V_{i,t-1} + \rho^* \widehat{V}_{i,t-1}^{*} + \gamma \Delta P_{i,t-1} + \gamma^* \Delta P_{i,t-1}^{*} + \varphi M_{i,t} + \boldsymbol{\zeta} \mathbf{F}_{i,t-1} + \pi f_i^{mortgage} r_{t-1} + \varepsilon_{i,t},$$

in the first case, and:

main residence outright and which are not part of a mortgage lending agreement, or which dispose of sufficient funds to purchase a property for cash. At the same time, even if large changes in interest rates make financial assets less desirable, the demand for housing should, if anything, increase, thereby biasing the estimated coefficients downwards and precluding any statistically significant effects.

$$V_{i,t} = \mu_i + \delta_t + \rho V_{i,t-1} + \rho^* \widehat{V}^*_{i,t-1} + \gamma \Delta P_{i,t-1} + \gamma^* \Delta P^*_{i,t-1} + \varphi M_{i,t} + \boldsymbol{\zeta} \mathbf{F}_{i,t-1} + \sum_{k=1}^{K} \pi_k f^w_{i,k} z_{t-1,k} + \varepsilon_{i,t},$$

in the second.

Importantly, the inclusion of both district-level and time period fixed effects insures that any possible unobserved common component contained in the two sets of interaction terms will be eliminated. The effects captured by the coefficient ρ^* will therefore be identified solely through the spatial heterogeneity in housing demand.

As in Badarinza and Ramadorai (2014), I measure the level of political risk in foreign countries using the monthly indicators from the International Country Risk Guide (ICRG) of political risk around the world. These indicators rate each country along 12 dimensions. For each country, I build a composite index by simply summing across these 12 risk categories and use weights based on the shares of respective populations in London to build time series for a set of nine world regions: Northern Europe and North America, Southern Europe, Eastern Europe, Asia-Pacific, South Asia, Africa, the Middle East, and South- and Central America. As constructed, the index ranges from 0 to 100, with 0 indicating the highest possible risk. I replace this with 100 minus the original values so that high levels of the index indicate high levels of risk and vice versa.

Finally, I use interest rates as proxies for aggregate macroeconomic and financial conditions between 1995 and 2013, namely the average rate on mortgage contracts issued by UK building societies. I retrieve this variable through Datastream.

I find that changes in borrowing conditions have a stronger effect on regions where mortgage indebtedness is more pervasive. I exploit this observation to show that the additional housing market liquidity associated with the relaxation of financial constraints spills over across neighbouring areas. Table A.1 documents significant spatial dependence between local turnover and the spatial average of the component of turnover which is associated with the changes in mortgage interest rates.

The presence of these spillovers is consistent with the idea that households use transaction prices to learn about market developments. Especially during the period before the crisis, characterized by low unemployment and increasing incomes, local housing markets were driven by a wide number of factors which generated the expectations of future house price increases. In the face of confounding factors, it is not surprising that the increases in housing demand associated with the relaxation of financial constraints have led to a more widespread perception of lower uncertainty and higher returns, which stimulated market activity and led to unprecedented levels of transaction volumes.

To the contrary, in the case of purchases by foreign buyers, which were heavily publicized in the media and discussed as determinants of regional asymmetries, no such effects are apparent. Households seem to have internalized the temporary and purely local nature of the higher market liquidity associated with the international demand for safe haven assets.

Table A.1

Spatial heterogeneity and the effects of increases in demand

The table reports estimated coefficients ρ^* from regression specifications of the form:

$$V_{i,t} = \mu_i + \delta_t + \rho V_{i,t-1} + \rho^* \widehat{V}^*_{i,t-1} + \gamma \Delta P_{i,t-1} + \gamma^* \Delta P^*_{i,t-1} + \varphi M_{i,t} + \boldsymbol{\zeta} \mathbf{F}_{i,t-1} + f_i^{mortgage} r_{t-1} + \varepsilon_{i,t},$$

in the first case, and:

$$V_{i,t}= \mu_i+\delta_t+\rho V_{i,t-1}+\rho^* \widehat{V}^*_{i,t-1}+\gamma \Delta P_{i,t-1}+\gamma^* \Delta P^*_{i,t-1}+\varphi M_{i,t}+\zeta F_{i,t-1}+ \sum_{k=1}^{K} f^w_{i,k} z_{t-1,k}+\varepsilon_{i,t},$$

in the second. Here, $\widehat{V}^*_{i,t}$ is obtained by projecting $V_{i,t}$ on the two sets of district-level spatio-temporal interaction terms capturing changes in borrowing conditions r_{t-1} and the effects of foreign demand, $\{z_{t-1,k}\}_{k=1,\dots,K}$ respectively. The estimation is restricted to the time period 1999 to 2006 in the first case and to the three regions London, South-East and East of England in the second. Driscoll-Kraay standard errors with 12 lags are shown in parentheses. The variables are normalized by subtracting the mean and dividing by the in-sample standard deviation. *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively.

		(1)	(2)
Spatial dependence	ρ^*	1.203***	0.026
		(0.390)	(0.028)

Appendix B

Figure A.1

Theoretical interpretation: feedback and acceleration mechanism

The figure illustrates the feedback and acceleration mechanism in housing market liquidity, arising in a framework in which households are rationally learning from price developments in neighbouring areas.

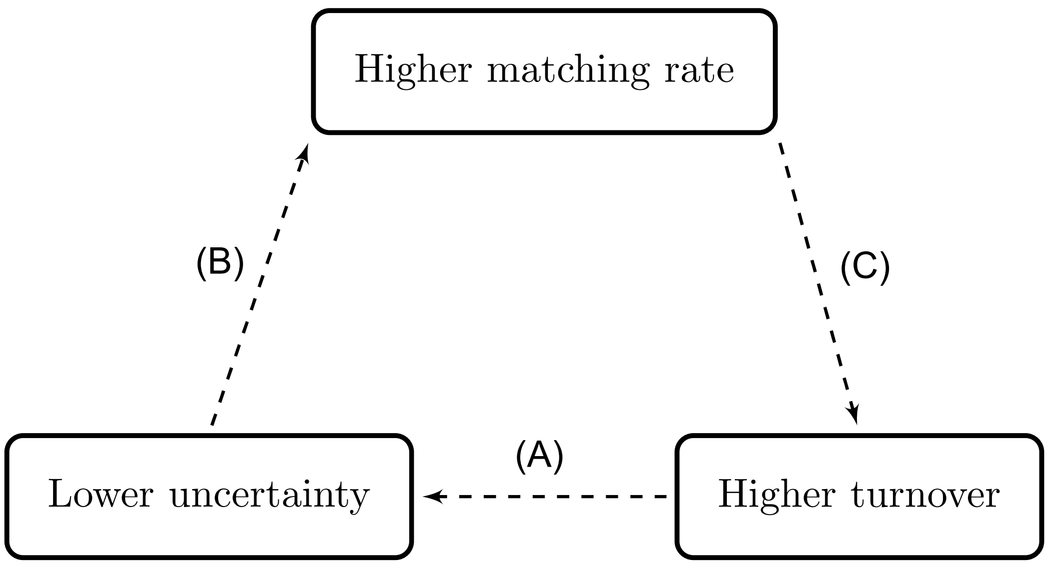

Table A.2

Structure of database fields

Panel A

Registry sample of housing transactions

Field	Desciption
Transaction ID	A reference number which is generated automatically recording each published sale
Price	Sale price stated on the transfer deed
Date of Transfer	Date when the sale was completed, as stated on the transfer deed
Postcode	7-digit postcode identifier
Property Type	D = Detached
	S = Semi-Detached
	T = Terraced
	F = Flats/Maisonettes
Old/New	Y = The property is newly built
	N = The property is an established residential building
Tenure	F = Freehold
	L = Leasehold

Panel B

British Household Panel Survey: Income dynamics and the general financial situation

Variable code	Description
wFIMN	**Total income - last month (in £per week)**
wFISIT	**Financial situation**
	How well would you say you yourself are managing financially these days? Would you say you are ...
	A: Living comfortably
	B: Doing alright
	C: Just about getting by
	D: Finding it quite difficult
	E: Finding it very difficult
wFISITX	**Financial expectations for year ahead**
	Looking ahead, how do you think you yourself will be financially a year from now, will you be ...
	A: Better than now
	B: Worse than now
	C: About the same

Figure A.2
Spatial weights for 'Oxford' Local Authority District

The figure illustrates a typical structure of the spatial weighting scheme, plotting the calculated weights ω_{ij} for the 'Oxford' district. The sum of the weights is equal to one and the district of origin itself is given a weight equal to zero. The weights are calculated as inverse fractions of distances between the geometric centres of the spatial coordinates of individual districts.

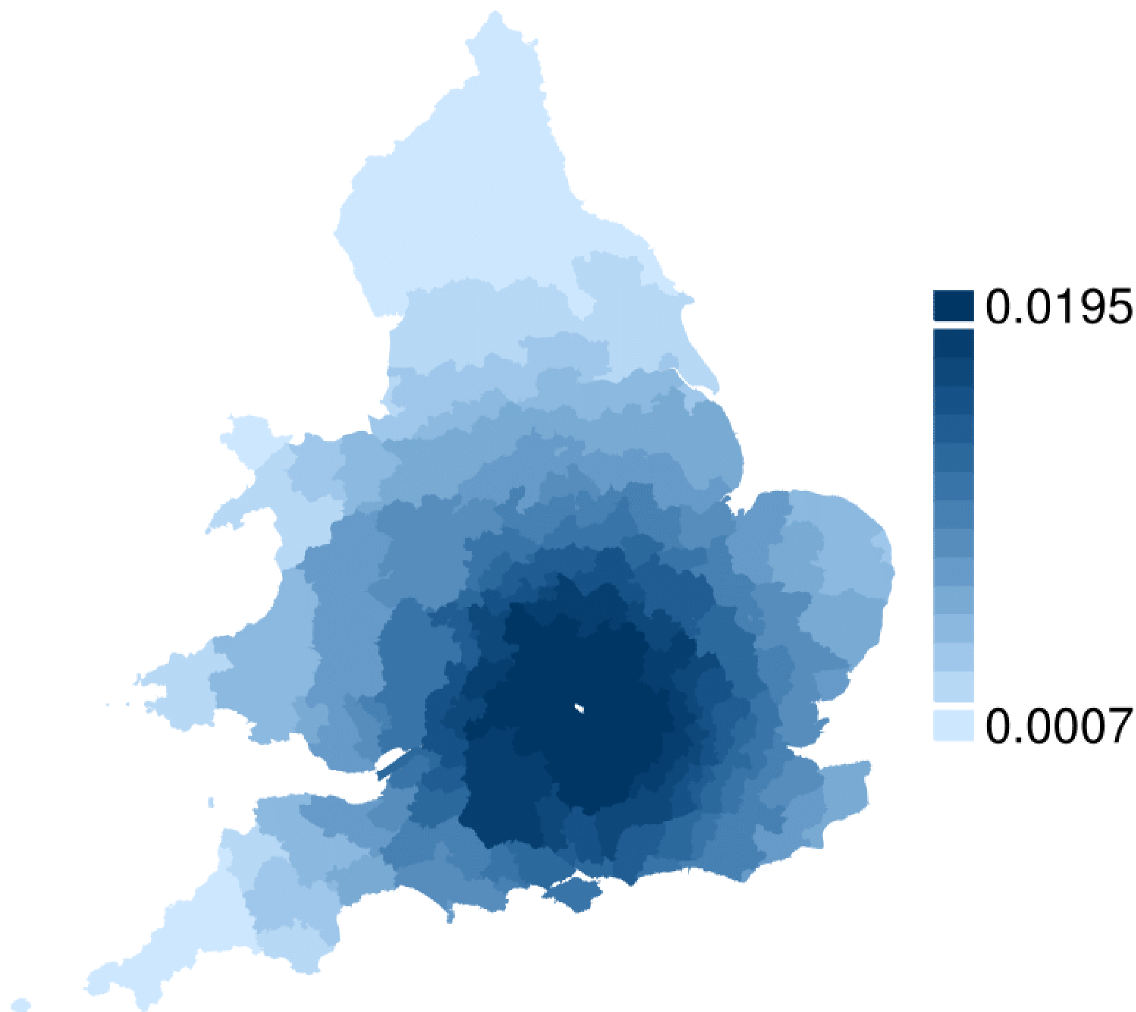

Figure A.3
Net district-level migration in 2013

The figure reports the estimated net migration flows, for each district in my sample. I calculate net quantities by subtracting population outflows from population inflows with a year. In order to obtain comparable values across districts, I normalize the net flows by dividing through the total population of the ward. The results can be interpreted as relative district-level net mobility within a year. The label "No Data" indicates the districts for which an assignment of district codes to the data provided by the Office for National Statistics as part of the Internal Migration Estimates is made infeasible by the 2009 administrative reorganization of the United Kingdom into Local and Unitary Authorities.

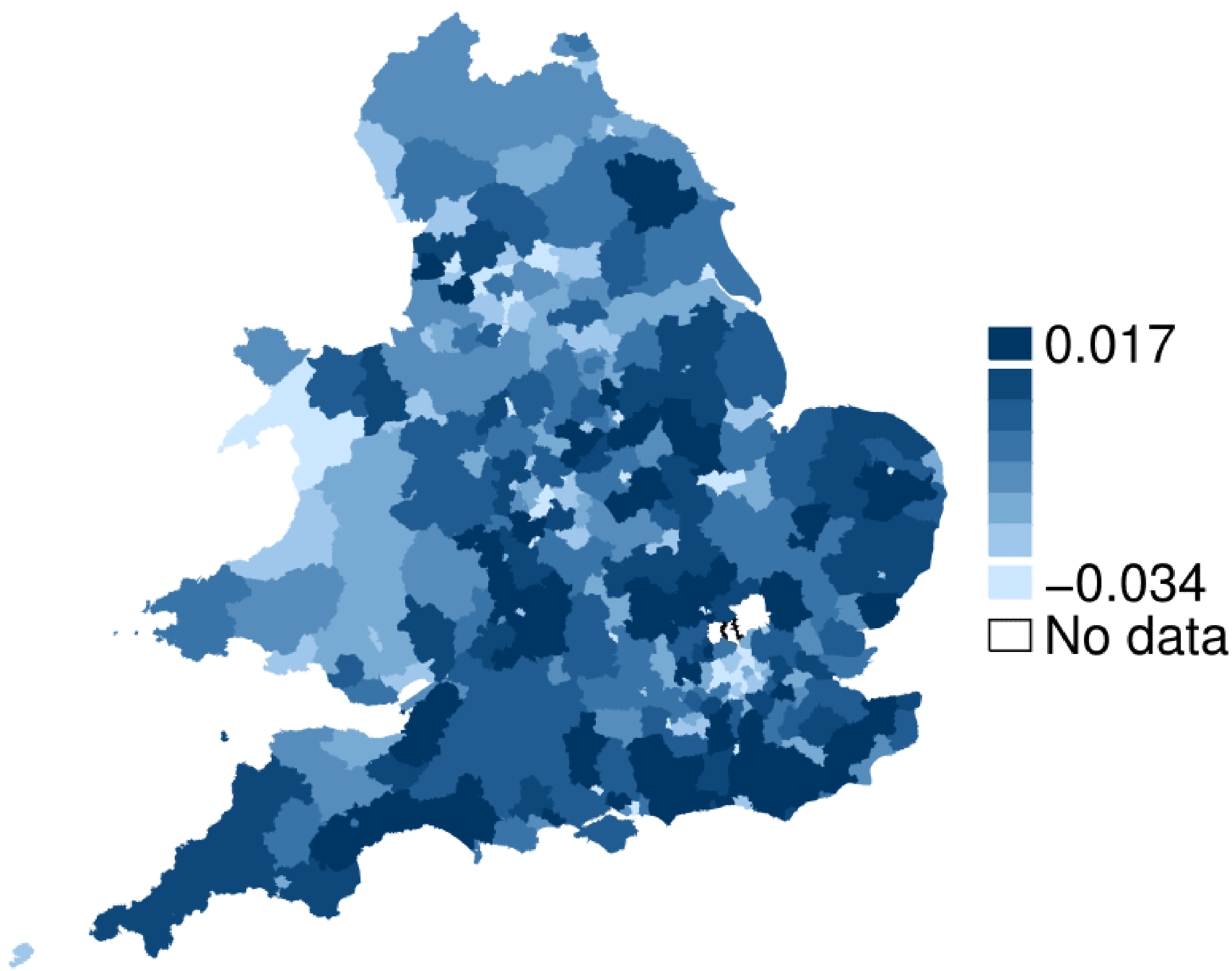

Figure A.4

Perceived vs. actual house price growth

The figure reports average perceived and realized house price changes, across the full sample of districts in my sample, for which both Land Registry transaction-level and BHPS survey data is available. The estimated house price growth rates are in annual terms. I calculate district-level changes in house prices by using a hedonic pricing model. The BHPS data ends in 2008, which explains the end point of the graphical representation.