UNIVERSITÀ DEGLI STUDI DI BERGAMO

Department of Economics

WORKING PAPERS

Spatial Spillovers Across Housing Market Cycles

Jungyoon Lee, Elena Manzoni, Ren Ren, Francesca Rossi

February 2026 - WP N. 37 Year 2026

Working papers – Department of Economics
n. 37

Spatial Spillovers Across Housing Market Cycles

Jungyoon Lee, Elena Manzoni, Ren Ren,
Francesca Rossi

Università degli Studi di Bergamo
2026

Spatial Spillovers Across Housing Market Cycles / Jungyoon Lee, Elena Manzoni, Ren Ren, Francesca Rossi.
Bergamo: Università degli Studi di Bergamo, 2026.
Working papers of Department of Economics, n. 37
ISSN: 2974-5586
DOI: 10.13122/WPEconomics_37

Progetto grafico: Servizi Editoriali – Università degli Studi di Bergamo
Università degli Studi di Bergamo
via Salvecchio, 19
24129 Bergamo
Cod. Fiscale 80004350163
P. IVA 01612800167

https://aisberg.unibg.it/handle/10446/320989

Spatial Spillovers Across Housing Market Cycles

Jungyoon Lee[a], Elena Manzoni[b], Ren Ren[c] and Francesca Rossi[d]

[a] *Royal Holloway, University of London* *

[b] *University of Bergamo*

[c] *University of Reading*

[d] *University of Verona* †

February 13, 2026

Abstract

We develop a theory of housing price spillovers based on price references, whereby learning about unobservable location attributes gives rise to spatial contagion in house prices. Our model predicts that expected price changes drive the strength of housing price spillovers across market cycles. While the theory predicts a self-reinforcing upward price spiral during the boom, spatial spillovers do not amplify downward movements in prices during the downturn. It also justifies the use of Spatial Autoregressive (SAR) models with row-normalized weight matrices based on geographical proximity. The model's prediction is supported by U.S. data from recent housing market boom (2018-2023) and bust (2007-2012).
JEL classifications: R31, R12, C21.

1 Introduction

A well-known stylised fact of the housing market is the interdependence of housing prices: changes in property values in one area influence prices in other areas.

*Lee and Ren gratefully acknowledge research support from the ESRC Grant No. ES/P011705/1.

†This paper is dedicated to the loving memory of Francesca Rossi.

Understanding how and why housing prices spill over across locations is important because the spillover effects of place-based policies can often be both unintentional and substantial (Autor et al., 2014; Biswas et al., 2021; Deng et al., 2022). Although housing price spillovers have been widely acknowledged, their underlying mechanisms are not yet fully understood. One strand of research suggests that the displacement of residents and capital can lead to the interconnectedness of housing markets (Chang and Dasgupta, 2022; Deng et al., 2022). For example, when housing prices of one location rise, housing demand for living or investment may be displaced to other locations, leading to price appreciation spillovers. Other studies focus on identifying the externality channel of housing price spillovers (Autor et al., 2014; Biswas et al., 2021; González-Pampillón, 2022; Ooi and Le, 2013). For example, new high-end housing supply and foreclosure sales are regarded as positive and negative amenities, respectively, which influence the prices of neighbouring properties.

This study contributes to the growing literature that explores another possibility: how an individual's housing decision is influenced by price references. In a seminal work utilising a novel dataset, Szumilo (2021) formalizes the price co-movements due to learning from peer properties' prices. Empirically, he uses a sample of properties that underwent only internal renovations to rule out price spillover effects from externality. As internal renovations are unobserved from outside, they cannot generate physical externality (e.g., improvements in the neighbourhood) and only change the price information. Szumilo (2021) importantly provides causal identification of the reference channel, and we complement his work by offering a model that sheds light on the determinants of the strength of such spillovers.

Giacoletti and Parsons (2023) suggest that the housing price spillovers, as a result of market friction, should be stronger when the market is less competitive. This is because market friction makes matching between buyers and sellers difficult, and more searching behaviors lead to stronger spillovers. With a similar rationale, Gargano et al. (2023) suggest that the spillover should be stronger where housing prices are expected to increase significantly, causing greater difficulty to match. Although their intuitions are insightful, their predictions and evidence focus on boom periods only.

However, the mechanisms at work during a housing market boom may not necessarily apply in a bust. It is well-documented that housing market booms and busts are not symmetric (Fischer et al., 2021; Guerrieri et al., 2012, 2013; Sinai, 2013). Thus, it is unknown, both theoretically and empirically, how the spillover magnitude varies with housing price declines.

This study contributes to the literature by showing that the strengths of housing price spillovers are driven by expected price changes across the market cycles. It formalizes a theory in which individuals determine their offer price for a house based on the current utility of consumption and expected capital gains. Individuals need to learn the values of unobserved location attributes from the transaction prices of nearby properties, which generates the learning/reference channel of housing price spillover. Our theory yields two key implications.

First, it predicts that housing price spillovers depend positively on expected housing price changes. In other words, locations with higher expected price appreciation (larger booms) are predicted to exhibit stronger spatial spillover effects. Conversely, during downturns, locations with larger expected price declines (more severe busts) are predicted to experience weaker spillovers than locations with more moderate expected declines. While the theory predicts a self-reinforcing upward price spiral during the boom, spatial spillovers do not amplify downward movements of housing prices during the downturn.

These predictions are supported by the recent US market boom (2018-2023) and bust (2007-2012) data, as presented in Section 3. We focus on three states with clearly contrasting accumulated housing price changes over the boom and bust: Florida, New York, and Illinois.[1] We note that Florida experienced the

[1] These states were chosen also due to sharing similar demographic profiles and each state having a

steepest rise during the boom and the deepest drop during the bust, highlighting its highly volatile housing market driven by known speculative demand. Notably, its estimated price spillover is the strongest among the three states during the upswing, which aligns with intuition. Conversely, during the downturn, its estimated spatial spillover is the weakest of the three states, a result that may seem counterintuitive but is consistent with our predictions. It is notable that this flipping pattern is not observed with New York or Illinois. Rather, the strength of the housing price spillover depends on the expected housing price changes, just as predicted by our theory. We check that our results are robust to excluding, or, only considering tracts of, the major cities to take into account the market competitiveness, which may also affect the price spillover strength (Giacoletti and Parsons, 2023). As this study offers the first theoretical prediction and empirical evidence of housing price spillovers during bust periods, it complements the existing literature (e.g.Giacoletti and Parsons (2023); Gargano et al. (2023)) by understanding the evolution of spillover strength across the whole market cycles.

Second, our economic model generates an empirical specification similar to the widely used spatial autoregressive (SAR) models, theoretically justifying the inclusion of the SAR element with practical guidance on the weight matrix choice. Hence, this study adds to the literature on spatial modelling of the housing market e.g. (Elhorst et al., 2014; Holly et al., 2011; Yang et al., 2018). Our theoretical model cautions against some alternative spatial models, such as spatial lagged X (SLX), which do not include the spatial autoregressive term. Our empirical SAR model selection is further validated by the model specification test of Lee et al. (2025). Lee et al. (2025) offers a test for SAR model specification that does not presume the direction of possible misspecification is known, and importantly covers possible spatial weight matrix misspecification.

---

single dominant city. They have also received much interest in housing market literature due to their economic significance. Their recent 5-year accumulated price gains in 2018-2023 boom were 73%, 43%, and 34%, in Florida, New York, and Illinois, respectively, while accumulated price declines during the 2007-2012 bust were −43%, −15%, and −23%, respectively.

The rest of the article is organised as follows. In Section 2, we present the economic model of a house buyer's offer price formation that gives rise to the spatial autoregressive model whereby the weight matrix is based on the geographical proximity of house locations and is row-normalized. In Section 3, we verify the model's predictions using US housing market data from the recent boom period 2018-2023 and bust period 2007-2012. Section 4 concludes.

2 Model

In this section, we provide the details of economic theory that justifies using SAR in econometric modelling of house prices. We assume that the price buyer/individual i is willing to pay for a house l at time t (P_{ilt}, henceforth) depends on (i) his/her utility of consumption in period t (denoted by V_{ilt} in the sequel), (ii) the sale price at $t+1$ (P_{lt+1}), and, (iii) a discount factor (δ). Note the absence of an individual subscript in the sale price P_{lt+1}, which distinguishes it from an offer price an individual i is willing to make (P_{ilt}). Henceforth, we index by l the location/house and we let h_l denote all observable characteristics of location/house, while g_l indicates unobservable features of the location. Both h_l and g_l are assumed to be time invariant. Finally, ε_{il} denotes an idiosyncratic, time-invariant, zero-mean individual preference, which is assumed independent and identically distributed (i.i.d.) across individuals. We thence assume

$$P_{ilt}(h_l, g_l) = V_{ilt}(h_l, g_l, \varepsilon_{il}) + \delta\mathbb{E}(P_{lt+1}(h_l, g_l)). \tag{2.1}$$

More specifically, we model that the individual utility $V_{ilt}(\cdot)$ appearing at the RHS of (2.1) depends on the observable characteristics h_l, the unobservable characteristics g_l, and the idiosyncratic component ε_{il}, via the relationship

$$V_{ilt} = S_t(h_l) \cdot (g_l + \varepsilon_{il}), \tag{2.2}$$

where $S_t(h_l)$ is the objective/common valuation of observable h_l, which is publicly known. As all observable house and location characteristics h_l are accounted for in $S_t(h_l)$, we assume that the idiosyncratic preference ε_{il} is identically distributed across different locations l. As will be made clear in the sequel, the sale price P_{lt} is the offer price of the winning bidder and hence reflects the maximum idiosyncratic preference.

Let τ be the expected rate of change/appreciation of house value per period, which in turn reflects macroeconomic income/wage growth expectation, giving rise to

$$S_{t+1}(h_l) = (1 + \tau)S_t(h_l).$$

On the other hand, δ is the usual discount factor that, in this context, reflects the relative weight given to future, the interest rate and also possible market frictions that may hinder the selling process. These market frictions include transaction costs, such as capital gains tax, stamp duty, and sales agent commissions, but also any market characteristic that may either prolong the sales process or induce a probability that the sale does not go through. All these frictions lower δ by reducing the net value of the sale, or by moving it far away in the future, or by reducing its likelihood. Finally, $\mathbb{E}(P_{lt+1}(h_l, g_l))$ is the expected sale price in period $t + 1$.

In this framework, individual i observes $V_{ilt}(\cdot)$, h_l and knows $S_t(\cdot)$, but s/he cannot distinguish between the noise/individual preference (ε_{il}) and the unobservable quality of the location (g_l). Thus, an estimate of g_l is needed to predict the future sale price. In order to estimate g_l, individual i observes the sale prices of other houses in the neighbourhood. For two locations l and k within an area (state/county/city), we thence assume

$$g_l = c + \eta_l, \;\; g_k = c + \eta_k, \;\; E(\eta_k) = E(\eta_l) = 0, \tag{2.3}$$

with $Cov(\eta_l, \eta_k) \geq 0$ being a decreasing function of the distance $d(l, k)$. Individual

i in location l observes sale prices at other locations $k = 1, ..., L$, $k \neq l$, along with the publicly known objective valuation of their observable characteristics: $\{P_{kt}(h_k, g_k), S_t(h_k)\}$.

Therefore, the price that buyer i is willing to offer to pay for house/location l is given by

$$P_{ilt}(h_l, g_l) = S_t(h_l) \cdot (g_l + \varepsilon_{il}) + \delta \mathbb{E}(P_{lt+1}(h_l, g_l)). \tag{2.4}$$

Iteration gives

$$P_{ilt}(h_l, g_l) = S_t(h_l) \cdot (g_l + \varepsilon_{il}) + \sum_{s=1}^{\infty} \delta^s E(S_{t+s}(h_l) \cdot (g_l + \max_d \varepsilon_{dl})), \tag{2.5}$$

where we have replaced the resale price $P_{lt+1}(h_l, g_l)$ with the offer price of the winning bidder who has the maximum idiosyncratic preference. Noting that $S_{t+s}(h_l) = (1 + \tau)^s S_t(h_l)$, one can therefore derive a *normalized* price for each house, as

$$p_{ilt}(g_l) := \frac{P_{ilt}(h_l, g_l)}{S_t(h_l)} = v_{il}(g_l) + \sum_{s=1}^{\infty} \delta^s (1 + \tau)^s \mathbb{E}(\max_d v_{dl}(g_l)), \tag{2.6}$$

where

$$v_{il} = v_{il}(g_l) := \frac{V_{ilt}}{S_t(h_l)} = (g_l + \varepsilon_{il})$$

is privately known to i, while $\mathbb{E}(\max_d v_{dl}(g_l))$ needs to be estimated. Let $\delta^* = \delta(1 + \tau)$ and denote by $\hat{g}_l$ the sample equivalent of the unknown g_l. Considering that the expected sale price depends on the idiosyncratic preference of the winning bidder, if we assume $|\delta^*| < 1$,[2] the normalized price in (2.6) can be rewritten as

$$p_{ilt}(g_l) = \frac{P_{ilt}(h_l, g_l)}{S_t(h_l)} = v_{il} + \sum_{s=1}^{\infty} (\delta^*)^s \left(\hat{g}_l + \mathbb{E} \left(\max_d \varepsilon_{dl} \right) \right). \tag{2.7}$$

[2] The assumption that $|\delta^*| < 1$ is quite realistic. Recall that δ models not only the intertemporal component characterized by the interest rate, but also all the market characteristics that make the sale process slower, riskier and more costly. Moreover, in this framework we assume for simplicity that δ^* stays fixed across time. If we allow δ^* to vary over time the series can converge even if δ^* is occasionally larger than 1 during a market boom.

Equation (2.7) holds true also for the normalized price of other houses in the neighbourhood. For a potential buyer j of house k, let $\hat{g}_k$ represent the estimated g_k, and the normalised offer price j is willing to pay is given by:

$$p_{jkt}(g_k) = v_{jk} + \frac{\delta^*}{1-\delta^*}\hat{g}_k + \frac{\delta^*}{1-\delta^*}\mathbb{E}\left(\underset{q}{\max}\varepsilon_{qk}\right), \tag{2.8}$$

where $v_{jk} = g_l + \varepsilon_{jk}$.

Now, denote by $p_{kt}(g_k)$ the normalized sale price of house/location k, which would have been the normalised offer price of the winning bidder whose preference is $\underset{q}{\max}\varepsilon_{qk}$. Assuming that $\mathbb{E}(\hat{g}_k) = g_k$, i.e. that each buyer forms an unbiased estimate of $\hat{g}_k$, we can write

$$\mathbb{E}(p_{kt}(g_k)) = \frac{1}{1-\delta^*}\left(g_k + \mathbb{E}\left(\underset{q}{\max}\varepsilon_{qk}\right)\right), \tag{2.9}$$

so that individual i's evaluation of g_k in terms of the sale price p_{kt} of house k is given by

$$\tilde{g}_k = (1-\delta^*)p_{kt} - \mathbb{E}\left(\underset{q}{\max}\varepsilon_{qk}\right). \tag{2.10}$$

Recall now that $\mathbb{E}(g_l) = \mathbb{E}(g_k)$, and that the covariance between g_l and g_k is not constant, but instead it depends on the distance between k and l. Thus, individual i can decide to form expectations by looking at prices in the neighbourhood, retrieving $\tilde{g}_k$ and giving more weight to $\tilde{g}_k$s, $k = 1, ..., L$ and $k \neq l$ pertaining to locations ks that are closer to l (i.e., with higher covariance). So, a good estimator for g_l could be

$$\begin{aligned}
\hat{g}_l &= \frac{1}{\sum_{k\neq l} Cov(l,k)}\left(\sum_{k\neq l}\tilde{g}_k Cov(l,k)\right) \\
&= \frac{1}{\sum_{k\neq l} Cov(l,k)}\left(\sum_{k\neq l}\left((1-\delta^*)p_{kt} - \mathbb{E}\left(\underset{q}{\max}\varepsilon_{qk}\right)\right) Cov(l,k)\right) \\
&= \frac{1}{\sum_{k\neq l} Cov(l,k)}\left(\sum_{k\neq l}(1-\delta^*)p_{kt} Cov(l,k)\right) - \mathbb{E}\left(\underset{d}{\max}\varepsilon_{dl}\right),
\end{aligned}$$

where the last equality follows trivially since $\mathbb{E}\left(\max_{d}\varepsilon_{dl}\right) = \mathbb{E}\left(\max_{q}\varepsilon_{qk}\right)$, from identical distribution of ε_{dl} across houses/locations and across agents, as mentioned above.

Hence, agent i's offer price becomes

$$\begin{aligned} p_{ilt}(g_l) &= v_{il} + \sum_{s=1}^{\infty} \delta^{*s} \left(\hat{g}_l + \mathbb{E}\left(\max_{j}\varepsilon_{jk}\right)\right) \\ &= v_{il} + \frac{\delta^*}{1-\delta^*} \frac{\sum_{k\neq l}(1-\delta^*)p_{kt}Cov(l,k)}{\sum_{k\neq l} Cov(l,k)} \\ &= v_{il} + \delta^* \frac{\sum_{k\neq l} p_{kt}Cov(l,k)}{\sum_{k\neq l} Cov(l,k)}, \end{aligned} \tag{2.11}$$

which clearly depends on the weighted average of all other locations' prices via the second term in (2.11). This is a notable guidance from economic theory on a key practical consideration of spatial econometric modelling. Empirical spatial econometric literature has a long-standing debate on the suitability of row-normalization. Row normalization imposes homogeneous total exposure to spatial spillovers, without allowing some central individuals/ individuals in dense areas to have a more prominent role compared to more peripheral ones (e.g., Neumayer and Plümper, 2016). In the context of the housing market, we have obtained a theory-motivated choice of row-normalized, geographical-proximity-based weight matrices, which, along with further specification testing mentioned earlier, strengthen the credibility of estimation results.

Turning to the application of (2.11) to data, econometricians can only observe the sale price, which is (2.11) for the winning bidder, i.e.

$$p_{lt} = (g_l + (max_d \varepsilon_{dl})) + \delta^* \sum_{k\neq l} W_{kl} p_{kt}, \tag{2.12}$$

and has therefore the following estimating equation

$$Y_{lt} = \alpha_l + \beta' X_{lt} + \lambda \sum_{k\neq l} W_{kl} Y_{kt} + u_{lt}, \quad \text{where} \quad \lambda = \delta(1+\tau), \tag{2.13}$$

where Y_{lt} is the house price of location l at time t and α_l is house/location fixed effect- one needs panel data set so that differencing across time periods can account for these fixed effects. X_{lt} are regressors that may explain unanticipated changes in the distribution of the preferences of the winning buyer. Above is indeed a SAR model with fixed effects. Note Y_{lt} is house prices that have been adjusted/normalised for observable house and location characteristics. In Section 3, we use time-invariant location characteristics X_l and include time-varying β_t so that $\beta_t' X_l$ is used instead of $\beta' X_{lt}$.[3]

Our economic model provides an intuitive interpretation of the strength of spatial spillover in the housing market, namely $\lambda = \delta(1 + \tau)$. Higher price growth expectation is linked to stronger spillover, suggesting that the housing market has a self-reinforcing mechanism of house price expectation and movement during boom periods. On the other hand, in a falling market, a larger expected price decline leads to weaker spatial spillovers, which suggests that the mechanism is not self-reinforcing during busts.[4] Another implication is that market frictions can work to reduce spillovers by lowering δ- if, for example, there is a greater tax associated with selling and purchasing houses, it would lower δ and hence reduce the strength of spillover.

3 Testable Implication/prediction

In this section, we check if the following testable implications from the model of house price determination of the previous section are supported by the data.

Implication: $\lambda = (1 + \tau)\delta$, higher expected growth rate of house prices (τ) leads

[3]In any given empirical setting, the practitioner can decide if inclusion of spatial lag terms of the covariates X_{lt} may be relevant, i.e. neighbouring locations' characteristics affect the distribution of individual buyers' preference of a given location, even after the location's own characteristics are accounted for.

[4]Two recent papers, Kaplan et al. (2020) and Ben-David et al. (2025), have both found that the housing boom and bust around the Great Recession were mostly driven by price expectations. Their findings echo our model's prediction that house price expectation is the major driver of house price movement over the market cycle.

to higher spillover strength λ, for a given discount factor δ.

When it comes to finding data for our purpose, we face the following challenges. As noted above, it is essential to allow for house/location fixed effects in (2.13), so we require panel data for differencing. For individual transaction data, this would require two repeated sales data for a given house and its neighbouring houses. Noting that houses do not get resold frequently and neighbouring houses typically have different sets of consecutive sale dates, it is challenging to estimate the SAR model (2.13) with transaction level data. Furthermore, $\lambda = (1+\tau)\delta$ likely changes significantly over time as the expected house price growth, τ, and the discount factor, δ, vary across time, our theory would caution against taking differences across a long time period or pooling different regions with contrary housing market conditions. These challenges limit our ability to gather a meaningfully sized transaction level dataset for our purpose.

Hence we turn to house price index at the most granular level in the US, census tract-level, from The Federal Housing Finance Agency (FHFA) house price index. Recall that the price in our estimating equation (2.13) needs to be normalised to adjust for different observable characteristics of houses. FHFA house price index is a weighted, repeat-sales index for single-family house prices measuring average price changes in repeat sales or refinancings on the same properties, and hence a reliably normalised index, in line with the normalised price p_{lt} in (2.12) of Section 2.

Noting that τ is the expected rate of house price growth perceived by the buyers, we expect that past and current house price movements, along with expected future wage/income changes, help form τ. Further formalization of how this expectation is generated is not attempted here, instead we pick three states with prolonged contrasts in their house price growth rates to see if the estimated λ conforms to the prediction of the theory.

We run the following first differenced regression, which is the first differenced version of (2.13):

$$\triangle \log hp_{it} = X_i \triangle \beta_t + \lambda \sum_{j=1}^{n} W_{ij} \triangle \log hp_{jt} + \alpha_t + u_{it}, \quad (3.1)$$

where i represents the census tract. There are many tracts without any house transactions for any given year, so the number of tracts vary over time. $\triangle \beta_t$ measures how the price premium of location characteristics (e.g., the preference of living close to the city center) changes over time.

We assume that each state in the US is one housing market with the common state-wide expected price rises or fall, which is capitalized into the housing prices via (2.4), resulting in (3.1). We recognize that this expectation for areas within larger cities may not hold for locations outside major urban centers, but our robustness checks produce comparable results. The assumption that house price expectation based on past market movement is incorporated into house price level is supported by survey evidence (Case et al., 2012; Piazzesi and Schneider, 2009; Kuchler et al., 2023) and is adopted in many studies (Glaeser et al., 2008; Glaeser and Nathanson, 2015, 2017; Huang and Tang, 2012). Thus, we envisage states' rankings in their accumulated price appreciation to represent also the ordering of their respective levels of market expectations. We calculated and ranked the accumulated price appreciation in all states during the recent boom of 2018-2023. We selected the states with relatively high, moderate, and low expected price appreciation based on their ranking in the realised returns, in spirit similar to Gargano et al. (2023). Among the states, we chose Florida (ranked 3/50), New York (ranked 22/50), and Illinois (ranked 41/50) as our sample of states with contrasting house price expectations. Their 5-year (2018-2023) accumulated price gains were 73%, 43%, and 34%, respectively. We focus on these three states because they share similar demographics (see Table 1), have a single famous/dominant city, and have attracted particular interest in housing market research due to their economic importance.[5] During the bust period of 2007-2012, accumulated price drops were -43%, -15%, and -23% in Florida, New York, and Illinois, respectively, allowing us to carry out a similar analysis of the magnitude of spatial spillovers across markets undergoing different severities of price declines. We expect to see the housing price spillover parameter λ among neighbourhoods of a market to be the largest in Florida and the smallest in Illinois ($\lambda_{FL} > \lambda_{NY} > \lambda_{IL}$) during the boom, while in the bust, we expect $\lambda_{NY} > \lambda_{IL} > \lambda_{FL}$.[6]

3.1 Data and Estimation

The focus on empirical analysis is to estimate the housing price spillover λ across tracts within each of the three states. As well as taking the first difference to allow for tract-level fixed effects, we also include some tract characteristics as control variables to account for within-state variations. These include the share of the white population (%White), the share of the population with university degrees (%Uni), and the share of households receiving public assistance (%PubAssist). These variables are taken from the American Community Survey of 2000 and 2010, corresponding to the bust (2007-2012) and boom (2018-2023) periods, respectively. These demographics with time lags are common control variables in housing price studies (Ferreira and Gyourko, 2012; Glaeser and Ward, 2009; Guerrieri et al., 2012) and the 7-8 year time lags are intended to ensure exogeneity of these controls. Tracts' proximity to city centres (CityCenter) is also included, as studies have shown real estate markets close to the city centres differ from the rest of the city (Glaeser et al., 2012; Rosenthal et al., 2022). CityCenter is a dummy variable, which equals one if the tract belongs to the 20% closest tracts to the city centre,

[5]For example, we did not choose California because it is not comparable to other two states. For example, it is the most populated state in the US and has multiple famous cities (i.e., Los Angeles and San Francisco).

[6]The average 30 year mortgage fixed rate in the US was 4.45% during 2018-2023 and 5.04% during 2007-2012, according to time series data MORTGAGE30US downloaded on 10 Jan 2025 from https://alfred.stlouisfed.org/series?seid=MORTGAGE30US. We assume δ does not differ much between the three states, since the interest rate is common at any given time and difference across states in relevant property-related tax levels are insignificant.

and zero otherwise. In the appendix, we present all results using an alternative threshold of 10%, which are similar to the results using the 20% threshold presented here. As cities may have more than one city centre, we also include residential market accessibility (RMA) to capture each tract's locational advantage more generally. The RMA is a measurement of job accessibility, and it is the sum of jobs available to each tract, weighted by commute time between the locations of jobs and the residential tract. The RMA measured in 2000 and 2010 are available from the published datasets of Baum-Snow and Han (2024) and are used for the bust (2007-2012) and boom (2018-2023) periods, respectively. Like the demographic variables, the 7-8 year time lag is intended to mitigate the potential endogeneity of CityCenter and RMA.

Summary statistics are given in Table 1, where Panels A, B, and C are for Florida, New York, and Illinois, respectively. The $\triangle\log(\text{HP})$ is the annual housing price changes of census tracts during the periods 2018-2023 and 2007-2012. The three states share similar demographics in terms of the proportion of the white ethnic population (%White), those receiving public assistance (%PubAssist), and those having a university degree (%Uni). It is not surprising to see that tracts in New York have the best job accessibility (RMA), followed by Illinois and then Florida. Big cities (i.e., New York City and Chicago) usually offer more job opportunities and better amenities. The city centre dummy variable (CityCenter) has the same mean of 0.2 across the three states, reflecting the definition of city centre dummy as the 20% most central tracts.

We estimate the model using spatial two-stage least squares (2SLS), following Kelejian and Prucha (1998), with spatial lags of the exogenous regressors serving as instruments, as is standard in the spatial econometrics literature. Identification relies on the exogeneity of the regressors, which include the shares of the White population (%White), the population with university degrees (%Uni), households receiving public assistance (%PubAssist), proximity to city centers (CityCenter), and Residential Market Accessibility (RMA). These variables are measured in 2010

Table 1: Summary Statistics

Panel A: Florida	BOOM (2018-2023)					BUST (2007-2012)				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
$\triangle$log(HP)	4661	0.11	0.08	-0.22	0.49	4882	-0.11	0.12	-0.79	0.31
%PubAssist	4661	0.01	0.01	0	0.11	4882	0.05	0.04	0	0.29
%White	4661	0.81	0.18	0.01	1	4882	0.86	0.15	0.04	1
%Uni	4661	0.29	0.14	0.06	0.78	4882	0.27	0.14	0.05	0.73
RMA	4661	590.25	191.4	130.86	863.93	4882	552.47	183.56	93.23	862.47
CityCenter	4661	0.2	0.4	0	1	4882	0.2	0.4	0	1
Panel B: New York	BOOM (2018-2023)					BUST (2007-2012)				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
$\triangle$log(HP)	6702	0.07	0.06	-0.45	0.41	7206	-0.03	0.05	-0.33	0.26
%PubAssist	6702	0.01	0.02	0	0.18	7206	0.05	0.04	0	0.37
%White	6702	0.81	0.22	0	1	7206	0.84	0.21	0.01	1
%Uni	6702	0.36	0.15	0.08	0.87	7206	0.32	0.15	0.07	0.85
RMA	6702	1294.39	655.34	127	2136.61	7206	1266.56	649.57	124.19	2068.8
CityCenter	6702	0.2	0.4	0	1	7206	0.2	0.4	0	1
Panel C: Illinois	BOOM (2018-2023)					BUST (2007-2012)				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
$\triangle$log(HP)	5851	0.06	0.06	-0.32	0.48	6073	-0.06	0.06	-0.49	0.34
%PubAssist	5851	0.02	0.02	0	0.11	6073	0.05	0.03	0	0.26
%White	5851	0.77	0.21	0	1	6073	0.82	0.19	0	1
%Uni	5851	0.33	0.19	0.01	0.89	6073	0.29	0.18	0.01	0.89
RMA	5851	1039.69	467.69	44.28	1577.14	6073	1023.29	470.47	52.44	1537.91
CityCenter	5851	0.2	0.4	0	1	6073	0.2	0.4	0	1

for the boom period (2018–2023) and in 2000 for the bust period (2007–2012). The 7–8 year lag between the regressors and the dependent variable—the change in log house prices, $\triangle \log hp_{it}$—is intended to mitigate concerns regarding endogeneity.

Although the economic modelling in Section 2 motivates the SAR model in (3.1) as the estimating equation for house prices, reliance on a specific parametric functional form and an exogenously specified spatial weight matrix leaves scope for arbitrary specification choices. To address this concern, we adopt the general specification tests proposed by Lee et al. (2025). Lee et al. (2025) introduce an omnibus specification test for SAR models that is agnostic to the direction of misspecification and, importantly, is capable of detecting misspecification of the spatial weight matrix. The null hypothesis of the test is correct SAR specification; rejection may occur in the presence of misspecification arising from spatial model selection, variable inclusion, functional form, or the choice of the spatial weight matrix. Their test is robust to heteroskedasticity of unknown form in the disturbance term. [7]

3.2 Empirical Evidence from the 2018-2023 Housing Boom

In this section, we take our testable implication that the magnitude of housing price spillover (λ) is positively related to the expected housing price growth rate (τ) to data. In a booming period, this implies that the spillover effects among neighbouring locations (e.g., census tracts) are stronger in a state or a city where a greater price appreciation is expected. Recall that the accumulated price appreciation during the boom (2018-2023) in Florida, New York, and Illinois is 73%, 43%, and 34%, respectively. As literature finds that achieved price rises are often extrapolated into future expectations, see e.g. Case et al. (2012); Piazzesi and Schneider (2009); Kuchler et al. (2023), we expect the estimated housing price spillover to be strongest among locations in Florida, followed by New York, and weakest in Illinois. Based on the estimating equation (3.1) derived from our economic modelling of house price determination in Section 2, we estimate the strength of housing spillover λ separately for the three states. In Table 2, we report the estimated λ, with vector X_i comprising of the five control variables mentioned earlier.[8] Their coefficients $\triangle\beta_t$ are the annual changes in location premium of the corresponding control. For example, the premium of city center proximity has been found to change over time in many studies (Brueckner et al., 2023; Davis et al., 2024;

[7] In an empirical application using Finnish municipal tax data, Lee et al. (2025) show that incorporating location fixed effects and applying their specification test yields estimation results that are closely aligned with those of Lyytikäinen (2012), who employ a policy-based instrumental variable rather than a spatial instrumental variable. Earlier spatial econometric studies relying on spatial IV approaches without location fixed effects had reached contrasting conclusions regarding regional tax competition; these findings were subsequently challenged by Lyytikäinen (2012) using a policy-based IV strategy. Lee et al. (2025) argue that such discrepancies likely stem from model misspecification in SAR frameworks, particularly the failure to account for location fixed effects, rather than problem of spatial IV.

[8] the share of the white population (%White), the share of the population with university degrees (%Uni), the share of households receiving public assistance (%PubAssist), the proximity to city centres (CityCenter) and Residential Market Accessibility (RMA) from 2010. For the bust period (2007-2012) considered in the next subsection, they were taken from 2000.

Delventhal et al., 2022; Gupta et al., 2022).

In Panel A, neighbouring locations are defined as the nearest eight census tracts. The elements w_{ij} in the spatial matrix W of (3.1) are one if location j is one of the nearest eight neighbouring locations of location i, zero otherwise. Panels B and C present λ estimates using the 16 and 24 nearest neighbour weight matrix, respectively. Columns 1 to 3 show the main results from the three states with all available tracts, while Columns 4 to 8 are robustness checks, after excluding tracts within or outside major cities (i.e., Miami, New York City and Chicago). For all cases considered, the omnibus specification test for the SAR model proposed by Lee et al. (2025) fails reject the models being fitted, offering further confidence in the estimation results in addition to the microfoundation of Section 2.[9]

We first look at the main results in columns 1 to 3 of Table 2. For example, in Panel B, among the nearest 16 neighbouring tracts, the estimated λ are 0.9194, 0.8068 and 0.6476 for Florida, New York and Illinois, respectively. This is in line with our prediction that $\lambda_{FL} > \lambda_{NY} > \lambda_{IL}$. The estimated spatial parameter λ is significantly positive, confirming the price dependence across nearby locations. Using alternative W matrices, the results from Panels A and C also conform with our prediction.

One may argue that the results may be driven by the big cities in the state, as the price movements and spillovers among neighbourhoods of big cities (more competitive markets) may not be the same as the rest of the state (Giacoletti and Parsons, 2023). Thus, we present the results after excluding tracts of Miami, New York City and Chicago in columns 4 to 6 of Table 2. Using Panel B as an example, the housing price spillover is significantly positive among the nearest 16 locations, and its magnitude follows our prediction that $\lambda_{FL} > \lambda_{NY} > \lambda_{IL}$. With alternative spillover domains of 8 and 24 neighbours, we obtain similar results in Panels A and C.

In columns 7 and 8 of Table 2, we present the results of tracts only from major

[9]see end of Section 3.1 for more discussions on the model specification test and estimation.

cities. Miami is excluded because the number of tracts with all available data is not sufficient for running the spatial models.[10] The λ estimates show that the housing price dependence among tracts of New York City and Chicago is significantly positive, and the magnitude of the spillover is stronger in New York City. For example, in Panel B, $\hat{\lambda}$ is 0.9388 in New York City and 0.6222 in Chicago. These results are robust in Panels A and C with alternative W matrices.

Table 2: Boom period 2018-2023: $\hat{\lambda}$, estimated with 20% City Center dummy

	all tracts			excl. major cities			cities only	
	FL	NY	IL	FL†	NY†	IL†	NYC	Chicago
Panel A: $W = NN8$								
$\hat{\lambda}$	0.759***	0.7348***	0.6347***	0.8143***	0.7124***	0.5982***	0.9551***	0.8304**
(t-stat)	(6.07)	(5.17)	(4.80)	(6.39)	(5.99)	(4.54)	(4.18)	(2.19)
R^2	0.5409	0.2648	0.3173	0.5394	0.2607	0.3511	0.1084	0.1535
Obs	4661	6702	5851	4600	5660	4871	1042	980
Panel B: $W = NN16$								
$\hat{\lambda}$	0.9194***	0.8068***	0.6476***	0.9582***	0.7395***	0.6581***	0.9388***	0.6222*
(t-stat)	(8.48)	(6.53)	(5.40)	(8.60)	(7.64)	(5.58)	(4.78)	(1.67)
R^2	0.5461	0.2789	0.3335	0.5451	0.2756	0.3647	0.1484	0.1787
Obs	4661	6702	5851	4600	5660	4871	1042	980
Panel C: $W = NN24$								
$\hat{\lambda}$	0.9433***	0.8760***	0.6643***	0.9727***	0.7741***	0.6743***	0.9968***	0.4104
(t-stat)	(8.81)	(7.07)	(5.31)	(8.68)	(8.06)	(5.88)	(4.73)	(1.20)
R^2	0.5489	0.2830	0.3329	0.5486	0.2798	0.3642	0.1557	0.1920
Obs	4661	6702	5851	4600	5660	4871	1042	980

Notes: † denotes estimates excluding major cities. Robust t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Florida, New York, and Illinois' 5-year (2018-2023) accumulated price gains were 73.07%, 42.84%, and 34.03%, respectively. Our theory predicts $\lambda_{FL} > \lambda_{NY} > \lambda_{IL}$.

3.3 Empirical Evidence from the 2007-2012 Housing Bust

In Section 3.2, we have shown that the housing price spillover λ is stronger where a bigger market boom is expected. Here, we test our theory's implication for a market downturn. Recall that λ is positively correlated with expected price changes. In a bust period, this means that the spillover effects among neighbouring locations are stronger in a state or a city with a smaller expected price decline (a milder

[10]over the periods, we have 61 observations for Miami, which equates to 12.2 observations per year on average, making it unlikely the sample contains relevant neighboring tracts.

bust). During 2007–2012, according to FHFA indices, the housing price drops were -43%, -15%, and -23% in Florida, New York, and Illinois, respectively. Thus, we expect to see that the housing price spillover λ is largest in New York, followed by Illinois, and smallest in Florida ($\lambda_{NY} > \lambda_{IL} > \lambda_{FL}$) during the bust period.

Similar to Table 2, Table 3 presents the estimates of λ for the three states using all available tracts (columns 1–3), tracts outside major cities (columns 4–6), and tracts within major cities (columns 7 and 8) based on (3.1). Spatial matrices of the nearest 8, 16, and 24 neighbours are used in Panels A, B, and C, respectively. The estimated λ is significantly positive in all models, showing that the price reference mechanism applies during market downturns. Regarding the magnitude, using columns 1–3 of Panel B as an example, the estimated λ is 0.6772, 0.4818, and 0.3332 in New York, Illinois, and Florida, respectively, which follows our prediction ($\lambda_{NY} > \lambda_{IL} > \lambda_{FL}$). This finding is robust when using alternative samples in columns 4–8 and alternative spatial matrices in Panels A and C.

Grounded in the price reference channel and the role played by expected housing price movements formalized in Section 2, our theoretical framework predicts that the intensity of the housing price spillover effect is positively related to expected housing price changes in both periods of market expansion and market contraction. Together with empirical support for this prediction from both the recent boom and bust phases of the U.S. housing market, our theory contributes to the literature on the mechanisms underlying housing price spillovers (Gargano et al., 2023; Szumilo, 2021), which has hitherto focused exclusively on booming periods.

4 Conclusion

In this paper, we offer a theoretical model of housing price spillover that lends justification to the choice of the SAR model with row-normalized weight matrix based on the geographical proximity of locations. The economic model impor-

Table 3: Bust period 2007-2012: $\hat{\lambda}$, estimated with 20% City Center dummy

	all tracts			excl. major cities			cities only	
	NY	IL	FL	NY†	IL†	FL†	NYC	Chicago
Panel A: $W = NN8$								
$\hat{\lambda}$	0.5693***	0.5244***	0.3486***	0.6442***	0.4680***	0.3530***	0.7573***	0.5955***
(t-stat)	(5.43)	(8.13)	(3.48)	(8.17)	(6.87)	(3.71)	(5.88)	(4.60)
R^2	0.3083	0.4917	0.4712	0.3194	0.4818	0.4721	0.2913	0.4673
Obs	7206	6073	4882	5940	5015	4818	1266	1058
Panel B: $W = NN16$								
$\hat{\lambda}$	0.6772***	0.4818***	0.3332***	0.6895***	0.3970***	0.3941***	0.8302***	0.5742***
(t-stat)	(6.41)	(7.90)	(2.68)	(8.94)	(6.16)	(3.44)	(6.46)	(4.99)
R^2	0.3131	0.4807	0.4694	0.3278	0.4715	0.4783	0.2936	0.4613
Obs	7206	6073	4882	5940	5015	4818	1266	1058
Panel C: $W = NN24$								
$\hat{\lambda}$	0.8321***	0.4359***	0.3108**	0.7398***	0.3489***	0.3998***	0.8396***	0.5032***
(t-stat)	(8.27)	(7.08)	(2.07)	(9.53)	(5.29)	(3.00)	(5.68)	(4.51)
R^2	0.3150	0.4728	0.4655	0.3322	0.4647	0.4779	0.2896	0.4535
Obs	7206	6073	4882	5940	5015	4818	1266	1058

Notes: † denotes estimates excluding major cities. Robust t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. New York, Illinois and Florida's 5-year (2007-2012) accumulated price changes were -15.20%, -34.03%, and -42.60% respectively. Our theory predicts $\lambda_{NY} > \lambda_{IL} > \lambda_{FL}$.

tantly facilitates the interpretation of the SAR coefficient in terms of economic factors, namely price expectation and discount factor, and is able to explain the evolution of spatial spillover strength throughout the whole market cycle. Our theory suggests that there is a self-reinforcing, expectation-driven upward contagion during housing booms, whereas spatial spillovers do not amplify the housing price declines of downturns.

A key testable implication of the model is that house price growth expectations govern the magnitude of spatial spillovers in housing markets. This implication is supported by U.S. data for both the recent boom period (2018-2023) and the bust period (2007-2012). The findings inform the design and timing of housing and macroprudential policies by emphasizing the role of expectations in driving spatial amplification during housing booms. They suggest that interventions are likely to be most effective when deployed early in the upswing, before expectations become self-fulfilling through spatial spillovers.

References

Autor, D. H., Palmer, C. J., and Pathak, P. A. (2014). Housing market spillovers: Evidence from the end of rent control in cambridge, massachusetts. *Journal of Political Economy*, 122(3):661–717.

Baum-Snow, N. and Han, L. (2024). The microgeography of housing supply. *Journal of Political Economy*, 132(6):1897–1946.

Ben-David, I., Towbin, P., and Weber, S. (2025). Inferring expectations from observables: Evidence from the housing market. *The Review of Economics and Statistics*, pages 1–17.

Biswas, A., Cunningham, C., Gerardi, K., and Sexton, D. (2021). Foreclosure externalities and vacant property registration ordinances. *Journal of Urban Economics*, 123:103335.

Brueckner, J. K., Kahn, M. E., and Lin, G. C. (2023). A new spatial hedonic equilibrium in the emerging work-from-home economy? *American Economic Journal: Applied Economics*, 15(2):285–319.

Case, K. E., Shiller, R. J., and Thompson, A. (2012). What have they been thinking? home buyer behavior in hot and cold markets. Technical report, Brookings papers on economic activity(FALL).

Chang, Y.-Y. and Dasgupta, S. (2022). Capital inflows and property prices: ethnicity, education, and spillovers. *Journal of Financial and Quantitative Analysis*, 57(8):3145–3177.

Davis, M. A., Ghent, A. C., and Gregory, J. (2024). The work-from-home technology boon and its consequences. *Review of Economic Studies*, 91(6):3362–3401.

Delventhal, M. J., Kwon, E., and Parkhomenko, A. (2022). Jue insight: How do cities change when we work from home? *Journal of Urban Economics*, 127:103331.

Deng, Y., Liao, L., Yu, J., and Zhang, Y. (2022). Capital spillover, house prices, and consumer spending: quasi-experimental evidence from house purchase restrictions. *The Review of Financial Studies*, 35(6):3060–3099.

Elhorst, J. P. et al. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*, volume 479. Springer.

Ferreira, F. and Gyourko, J. (2012). Heterogeneity in neighborhood-level price growth in the united states, 1993–2009. *American Economic Review*, 102(3):134–140.

Fischer, M., Füss, R., and Stehle, S. (2021). Local house price comovements. *Real Estate Economics*, 49(S1):169–198.

Gargano, A., Giacoletti, M., and Jarnecic, E. (2023). Local experiences, search, and spillovers in the housing market. *The Journal of Finance*, 78(2):1015–1053.

Giacoletti, M. and Parsons, C. A. (2023). Reference points spillovers: Micro-level evidence from real estate. *The Review of Financial Studies*, 36(11):4636–4676.

Glaeser, E. L., Gottlieb, J. D., and Tobio, K. (2012). Housing booms and city centers. *American Economic Review*, 102(3):127–133.

Glaeser, E. L., Gyourko, J., and Saiz, A. (2008). Housing supply and housing bubbles. *Journal of urban Economics*, 64(2):198–217.

Glaeser, E. L. and Nathanson, C. G. (2015). Housing bubbles. In Henderson, J. V. and Strange, W. C., editors, *Handbook of regional and urban economics*, volume 5, pages 701–751. Elsevier.

Glaeser, E. L. and Nathanson, C. G. (2017). An extrapolative model of house price dynamics. *Journal of Financial Economics*, 126(1):147–170.

Glaeser, E. L. and Ward, B. A. (2009). The causes and consequences of land use regulation: Evidence from greater boston. *Journal of urban Economics*, 65(3):265–278.

González-Pampillón, N. (2022). Spillover effects from new housing supply. *Regional Science and Urban Economics*, 92.

Guerrieri, V., Hartley, D., and Hurst, E. (2012). Within-city variation in urban decline: The case of detroit. *American Economic Review*, 102(3):120–126.

Guerrieri, V., Hartley, D., and Hurst, E. (2013). Endogenous gentrification and housing price dynamics. *Journal of Public Economics*, 100:45–60.

Gupta, A., Mittal, V., Peeters, J., and Van Nieuwerburgh, S. (2022). Flattening the curve: pandemic-induced revaluation of urban real estate. *Journal of Financial Economics*, 146(2):594–636.

Holly, S., Pesaran, M. H., and Yamagata, T. (2011). The spatial and temporal diffusion of house prices in the uk. *Journal of urban economics*, 69(1):2–23.

Huang, H. and Tang, Y. (2012). Residential land use regulation and the us housing price cycle between 2000 and 2009. *Journal of Urban Economics*, 71(1):93–99.

Kaplan, G., Mitman, K., and Violante, G. L. (2020). The housing boom and bust: Model meets evidence. *Journal of Political Economy*, 128(9):3285–3345.

Kelejian, H. H. and Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The journal of real estate finance and economics*, 17(1):99–121.

Kuchler, T., Piazzesi, M., and Stroebel, J. (2023). Housing market expectations. In *Handbook of economic expectations*, pages 163–191. Elsevier.

Lee, J., Phillips, P. C., and Rossi, F. (2025). Heteroskedasticity robust specification testing in spatial autoregression. *Econometric Theory*, 41(5):995–1043.

Lyytikäinen, T. (2012). Tax competition among local governments: Evidence from a property tax reform in finland. *Journal of Public Economics*, 96(7-8):584–595.

Neumayer, E. and Plümper, T. (2016). Spatial spill-overs from terrorism on tourism: Western victims in islamic destination countries. *Public Choice*, 169(3):195–206.

Ooi, J. T. and Le, T. T. (2013). The spillover effects of infill developments on local housing prices. *Regional Science and Urban Economics*, 43(6):850–861.

Piazzesi, M. and Schneider, M. (2009). Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review*, 99(2):406–411.

Rosenthal, S. S., Strange, W. C., and Urrego, J. A. (2022). Jue insight: Are city centers losing their appeal? commercial real estate, urban spatial structure, and covid-19. *Journal of Urban Economics*, 127:103381.

Sinai, T. M. (2013). House price moments in boom-bust cycles. In Glaeser, E. and Sinai, T. M., editors, *Housing and The Financial Crisis*. University of Chicago Press, Chicago.

Szumilo, N. (2021). Prices of peers: Identifying endogenous price effects in the housing market. *The Economic Journal*, 131(639):3041–3070.

Yang, J., Yu, Z., and Deng, Y. (2018). Housing price spillovers in china: A high-dimensional generalized var approach. *Regional science and urban economics*, 68:98–114.

Appendix

This appendix contains Tables 4-5 that report estimation results with 10% City Center dummy.

Table 4: Boom period 2018-2023: $\hat{\lambda}$, estimated with 10% City Center dummy

	all tracts			excl. major cities			cities only	
	FL	NY	IL	FL†	NY†	IL†	NYC	Chicago
Panel A: W = NN8								
$\hat{\lambda}$	0.7500***	0.6830***	0.5274***	0.8078***	0.7054***	0.4952***	0.9052***	0.7015*
(t-stat)	(6.01)	(4.84)	(3.66)	(6.38)	(5.93)	(3.64)	(4.26)	(1.75)
R^2	0.5417	0.2693	0.3229	0.5402	0.2619	0.3559	0.1148	0.1723
Obs	4661	6702	5851	4600	5660	4871	1042	980
Panel B: W = NN16								
$\hat{\lambda}$	0.9131***	0.7937***	0.5384***	0.9529***	0.7455***	0.4866***	0.9232***	0.4768
(t-stat)	(8.37)	(6.49)	(4.03)	(8.54)	(7.63)	(3.80)	(4.52)	(1.27)
R^2	0.5468	0.2799	0.3346	0.5458	0.2760	0.3654	0.1480	0.1967
Obs	4661	6702	5851	4600	5660	4871	1042	980
Panel C: W = NN24								
$\hat{\lambda}$	0.9338***	0.8764***	0.5418***	0.9658***	0.7828***	0.4892***	0.9727***	0.2565
(t-stat)	(8.64)	(7.36)	(4.03)	(8.55)	(8.04)	(4.01)	(4.29)	(0.74)
R^2	0.5496	0.2837	0.3337	0.5492	0.2806	0.3642	0.1545	0.2094
Obs	4661	6702	5851	4600	5660	4871	1042	980

Notes: † denotes estimates excluding major cities. Robust t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Florida, New York, and Illinois' 5-year (2018-2023) accumulated price gains were 73.07%, 42.84%, and 34.03%, respectively. Our theory predicts $\lambda_{FL} > \lambda_{NY} > \lambda_{IL}$.

Table 5: Bust period 2007-2012: $\hat{\lambda}$, estimated with 10% City Center dummy

	all tracts			excl. major cities			cities only	
	NY	IL	FL	NY†	IL†	FL†	NYC	Chicago
Panel A: W = NN8								
$\hat{\lambda}$	0.5021***	0.5155***	0.3496***	0.6307***	0.4883***	0.3494***	0.7452***	0.5721***
(t-stat)	(4.27)	(7.88)	(3.47)	(7.98)	(7.32)	(3.62)	(5.73)	(4.29)
R^2	0.3044	0.4912	0.4711	0.3198	0.4832	0.4712	0.2922	0.4729
Obs	7206	6073	4882	5940	5015	4818	1266	1058
Panel B: W = NN16								
$\hat{\lambda}$	0.6207***	0.4592***	0.3618***	0.6655***	0.4415***	0.4110***	0.8212***	0.5426***
(t-stat)	(4.90)	(7.34)	(2.91)	(8.32)	(7.15)	(3.56)	(6.33)	(4.65)
R^2	0.3103	0.4790	0.4727	0.3278	0.4753	0.4797	0.2955	0.4683
Obs	7206	6073	4882	5940	5015	4818	1266	1058
Panel C: W = NN24								
$\hat{\lambda}$	0.8893***	0.4112***	0.3225**	0.7107***	0.4420***	0.4090***	0.8368***	0.4879***
(t-stat)	(7.62)	(6.58)	(2.14)	(8.64)	(7.38)	(3.02)	(5.66)	(4.40)
R^2	0.3133	0.4706	0.4668	0.3321	0.4726	0.4784	0.2912	0.4604
Obs	7206	6073	4882	5940	5015	4818	1266	1058

Notes: † denotes estimates excluding major cities. Robust t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. New York, Illinois and Florida's 5-year (2007-2012) accumulated price changes were −15.20%, −34.03%, and −42.60% respectively. Our theory predicts $\lambda_{NY} > \lambda_{IL} > \lambda_{FL}$.