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Time-varying Persistence of House Price Growth: The Role of Expectations and Credit Supply[*]

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Abstract

High persistence is a prominent feature of price movements in U.S. housing markets, i.e., house prices grow faster this period if they grew faster last period. This paper provides two additional new insights to the literature on U.S. house price movements. First, there exists a significant time variation in the persistence of house price growth, both at the national and city level. Second, there is considerable heterogeneity in the time-varying persistence across different regions, particularly in areas that were historically less persistent, such as the capital-poor regions in the Midwest and South. This study conducts additional regression analyses to determine the main factor behind the time-varying persistence, with a particular focus on two housing demand factors: *extrapolative expectations* and *credit supply expansion*. Our results suggest that the time variation in the persistence of urban house price growth is better aligned with credit supply expansion than with extrapolative expectations. These findings remain robust even when accounting for potential endogeneity and reverse causality concerns.

Keywords: Persistence, House prices, Time variation, TVP-SV-AR model, Credit supply, Expectations, U.S. Cities.

JEL Classification: C22, G10, R12, R21

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"*Home prices have a lot of inertia and momentum, which makes housing markets more forecastable than stock markets.*" - Robert Shiller, at the AREUEA Policy Forum on Nov 16, 2022.

1 Introduction

As highlighted in the opening quote of the paper, high persistence is a prominent feature of the house price movement in the U.S. housing markets.[1] Since the pioneering work of Case and Shiller (1989), extensive empirical research on house price dynamics has consistently shown strong persistence in house price growth in the U.S., regardless of location, time period, or price index measurement (e.g., Ghyles et al., 2013; Guren, 2018; Schindler, 2013; Titman et al., 2014). For instance, Ghyles et al. (2013) observe a high serial correlation of growth rates in widely-used national house price indexes, such as 0.939 for the Case-Shiller index and 0.756 for the Federal Housing Finance Agency (FHFA) monthly house price index (HPI).[2] To interpret, if house prices grow faster in the current period, they are likely to grow faster in the next period, with current price growth serving as a useful predictor of future house price movements.

Despite the widespread agreement regarding the high persistence of house price growth, few studies have examined whether and indeed how this persistence varies over time. Unsurprisingly, far less is known about the underlying driving forces behind it. Given the significant structural changes that housing markets have undergone in the U.S., it is unlikely that house price persistence has remained stable over time. To illustrate this point, Figure 1 displays the persistence of the FHFA's U.S. national house price growth since 1982, estimated by the sum of autoregressive coefficients (SARC) in an autoregressive (AR) model for 12-year rolling windows.[3] The graph reveals a nontrivial variation over time in the persistence of U.S. national house price growth. The SARC estimate began to rise in the mid-1990s, reached its peak in the early 2000s, and subsequently remained relatively stable thereafter. Notably, the remarkable increase in persistence occurred before the onset of the 2000s housing cycle. The apparent time-varying behavior of persistence suggests that estimating persistence at a single point could be deceptive, and the often cited high persistence of house price growth in the literature

[1] In the literature, the term 'persistence' is often interchangeably used with 'momentum' and 'serial/auto-correlation'. In this paper, we stick to the term 'persistence' to refer to the extent of the response of house prices to shocks.

[2] Urban house price growth in the U.S. also exhibits high persistence, with a serial correlation of around 0.7 (Schindler, 2013). Refer to Ghyles et al. (2013) for an excellent overview of the discussion on the persistence of house price growth.

[3] The numbers on the horizontal axis in Figure 1 denote the starting point of 12-year rolling windows. Year 1995, for instance, represents the subsample period of 1995-2006, and so on. The SARC for national house price growth is estimated using the Hansen's (1999) 'grid bootstrap' based median-unbiased (MUB) estimator. See Appendix A for a further discussion on the SARC.

could be due to ignoring this temporal variation.[4]

Understanding the variation in the persistence of house price growth over time is crucial for several reasons. First, house prices have significant implications for various aspects of the economy, including household consumption (Berger et al., 2018; Choi and Jo, 2023), monetary policy (Cumming and Hubert, 2022)[5], and labor mobility and employment (Ferreira et al., 2010). Hence, understanding how and why house prices exhibit different levels of persistence at different times is crucial for assessing the impact of housing markets on the economy. Second, the persistence of house price growth implies an enduring influence of housing market shocks on the economy. If house price growth persists differently over time, then the shocks in housing markets will have varying impacts on the duration and magnitude of the housing cycle over time. This can lead to an extended period of increasing house prices even following a collapse in financial conditions, posing an additional challenge to monetary policymakers by introducing greater uncertainty and complexity into their decision-making processes. Third, the persistence of house price growth at the regional level can result in a geographic divergence of house prices, increasing the geographic inequality of economic well-being over time through its influence on household wealth and consumption (e.g., Choi et al., 2020). Fourth, high persistence of house price growth means a long-lasting deviation of house prices from fundamentals before the subsequent adjustments, which is conceptually related to the (self-fulfilling) housing bubble (e.g., Phillips et al., 2015). The presence of time-varying persistence in house price growth will make the occurrence and duration of housing bubbles more unpredictable.

For these reasons, we view the time-varying persistence as another prominent feature of the U.S. housing markets that warrants further investigation. Despite its potential significance, however, no previous research has pursued this line of inquiry or provided any concrete explanations for its drivers.[6] The primary objective of this study is to fill this research gap. While the visual evidence presented in Figure 1 is compelling, it may not be rigorous enough to establish time variation in persistence as a new empirical regularity. Hence, our analysis seeks to provide more formal evidence on the time-varying persistence of house price growth. The present study also aims to explore the factors driving the time-varying persistence through rigorous econometric analyses. To this end, we analyze the movements in national and urban house prices in the U.S. over the past four decades, utilizing

[4]Structural shifts, or variations over time in mean or persistence, are known to induce an upward bias on persistence as measured by standard AR models assuming a constant mean (e.g., Ang and Timmermann, 2013; Choi and Moh, 2007).

[5]According to Cumming and Hubert (2022), the heterogeneous impact of monetary policy on consumption depends on house price persistence, possibly through the refinancing channel in the transmission of monetary policy.

[6]To be precise, possible time variation in house price growth persistence was occasionally mentioned in earlier works (e.g., Gu, 2002; Beracha and Skiba, 2011), but none of them has investigated this issue further as is done here.

data from the FHFA's HPI.

Our analysis proceeds in two stages. In the first stage, we estimate time variation in house price persistence using a time-varying parameter (TVP) model with stochastic volatility (SV). Originally proposed by Primiceri (2005) to capture time-varying behavior of inflation series, the TVP model permits us to track changes in both persistence and volatility over time in a flexible and robust manner. Given the close link between macroeconomic cycles and housing cycles (e.g., Leamer, 2007), this econometric model is well-suited for our purposes. We are unaware of any prior research that employs the TVP-SV-AR model to estimate time-varying persistence of house price growth, especially at the subnational level.[7]

In the second stage of our analysis, we explore the factors driving the time-varying persistence of house price growth in the framework of panel data regression analyses. Because house prices are ultimately determined by the interplay of housing supply and demand, the magnitude of house price growth persistence is likely affected by the persistence of demand shocks as well as the elasticity of supply response (Titman et al., 2014). Some studies, however, have shown that traditional demand fundamentals such as income and population density do not fully explain the persistent movements in house prices, especially during the house price cycle in the 2000s (e.g., Glaeser et al., 2012; Head et al. 2014).[8]

Among the various factors discussed in the literature (see Table 1), we focus on two demand-side factors that have increasingly been recognized as influential in the housing boom-bust cycle of the 2000s: extrapolative expectations and credit supply expansion (e.g., Cox and Ludvigson, 2021; Griffin et al., 2021).[9]

Intuitively, extrapolative expectations can contribute to persistence owing to the strong influence of recent house price changes on housing market expectations (e.g., Case and Shiller, 1987; Case et al. 2012; Glaeser and Nathanson, 2017). Also, the role of credit supply expansion, typically driven by

[7] Guirguis et. at. (2005) applied a TVP-AR model to the U.S. national house price and found considerable parameter instability. Christou et al. (2019) also used a TVP-VAR model to study the impact of uncertainty shocks on the U.S. housing market. Relatedly, Aastveit et al. (2023) utilized a structural VAR model with TVP and SV (TVP-SV-VAR) and found some evidence of time variation in the Fed's response to house prices. None of these studies, however, focus on the persistence of house price growth.

[8] The movements of fundamentals, such as income and population density, are neither large enough to reconcile with the observed time variation in persistence of house price growth, nor do they explain the geographical heterogeneity in the evolution of persistence.

[9] As outlined in Table 1, alongside the two factors under consideration, the literature documents a broader set of factors behind the high persistence of house price growth. These include search and information frictions (e.g., Head et al., 2014), the presence of diverse beliefs and momentum traders (e.g., Piazzesi and Schneider, 2009), and strategic complementarities (e.g., Guren 2018). Despite their potential importance, these factors are not considered here, primarily due to limited understanding of their time-varying dynamics and the lack of geographic-level data measurements.

financial innovations or deregulations, has garnered enormous attention from researchers in explaining high persistence of house price growth (e.g., Favara and Imbs, 2015; Mian and Sufi, 2009, 2022). In this study, we run a panel data regression by relating the persistence of 279 MSA house prices estimated from the TVP-SV-AR model to a set of city-level characteristics that are related to the two housing demand factors under comparison, which is similar in spirit to the two-step approach employed in Gorodnichenko and Talavera (2017).

Our study reveals several important findings. First, we find evidence of significant time variation in the persistence of house price growth at the national and urban levels. Over the past four decades, the persistence of national house price growth has steadily increased, particularly since the mid-1990s. This observation aligns with the theoretical proposition of Gelain and Lansing (2014) that the persistence of house price growth should vary over time to accurately reflect the dynamics of the housing market. Second, the magnitude of persistence varies widely across different locations and periods. Interestingly, the rise in persistence is especially noticeable in cities located in the South and Midwest states that previously exhibited lower levels of persistence, slower house price growth rates, and fewer housing supply restrictions. This geographic heterogeneity is informative about the driving forces behind the time-varying persistence of house price growth. Third, the observed time-varying behavior of house price persistence is better aligned with the credit supply channel, possibly through banking integration and mortgage securitization, rather than by the extrapolative expectations channel. An increase in credit availability, proxied by per capita bank deposit growth, is meaningfully linked to an increased persistence of urban house price growth. By contrast, extrapolative expectations, proxied by previous house price growth, do not show a significant association with changes in house price growth persistence. Furthermore, our study finds that the influence of credit supply or expectations is not necessarily stronger in cities facing more stringent housing supply constraints. As further discussed in Section 5.3, however, this finding does not necessarily refute the widely documented (direct) positive impact of housing supply constraints on persistence (e.g., Lai and Van Order, 2017; Oikarinen et al., 2018). Our findings are robust to the use of instruments for endogeneity concerns based on city-level Bartik type instruments for credit supply.

The paper proceeds as follows. The next section presents a brief literature review on the recent debate surrounding the driving forces behind house price growth persistence. In Section 3, we provide an overview of the data and present some summary statistics of the key variables under study. Section 4 introduces the TVP-SV-AR model and applies it to estimate national house price growth. In Section 5, we extend our analysis to encompass nine Census divisions and 279 urban house prices and conduct a series of regression analyses to identify the factors influencing the time-varying persistence. In this section, we also examine the robustness of our findings to endogeneity concerns using city-level Bartik type instruments. Additionally, we assess the role of housing supply constraints in explaining the geographic heterogeneity observed in the influence of credit supply and expectations on time-varying persistence. Finally, Section 6 provides a conclusion to the paper. The Appendix provides supplementary information on the measure of persistence (SARC) and the measure of housing supply constraints employed in the current study. The Appendix also presents additional estimation results of the TVP-AR-SV models and the discussion of two popular panel data regression approaches.

2 Related literature

The persistence of house price growth has been extensively studied (see Table 2 for a partial list). To date, however, the analysis has been largely fragmentary due to differences in time periods and methodologies used, and the drivers of house price growth persistence remain a topic of debate. Additionally, existing research has neither explored the stability of persistence over time, nor provided explanations for its time-varying nature.

In theory, changes in house prices should reflect changes in both housing supply and demand. Therefore, the persistence of house price growth can be influenced by housing market characteristics related to demand (e.g., business cycle, income, and population) and supply (e.g., regulation and geographic constraints) as well as basic market features (e.g., illiquidity, information and transaction costs, and nonstandardized property), as summarized in Table 2. Due to the slow adjustments of housing supply factors, however, demand factors are often viewed as the primary driver of house price movements (Head et al., 2014).[10] Despite the literature suggesting that demand-side factors largely drive house price changes in the U.S., the specific factors responsible for time variation in persistence remain elusive. Moreover, empirical evidence suggests that conventional housing demand fundamentals alone are insufficient to explain the observed changes in house prices, particularly during the recent boom-bust cycle (e.g., Case and Shiller, 1989; Capozza et al., 2004).[11] Recent research focuses on two demand-side factors as drivers of the 2000s housing boom-bust cycle: extrapolative expectations

[10] Housing supply constraints, such as regulations, restrictive planning law and limited provision of building areas, affect persistence mainly through a temporal mismatch of demand and supply. As a result, changes in demand factors, even when they are not highly persistent, can still cause high persistence in house price changes if supply is not able to respond appropriately to the demand changes.

[11] For a dissenting view, see Chodorow-Reich et al. (2021) who claim that the 2000s housing boom-bust-rebound cycle was mainly driven by fundamental factors. Their focus, however, is placed on the housing cycles instead of the persistence of house price growth.

and credit supply expansion (e.g., Cox and Ludvigson, 2021; Kuchler et al., 2023). While there is an ongoing debate about which of the two factors is the main driver (e.g., Griffin et al., 2021; Howard and Liebersohn, 2023), investigating their relevance in explaining the time-variation in persistence found in our data seems worthwhile.[12]

Expectations are a plausible determinant of house price dynamics because individuals often rely on recent price changes when forming expectations about future prices. Extrapolative backward-looking expectations are therefore frequently cited as a potential cause of persistence (e.g., Case and Shiller, 1987; Glaeser and Nathanson, 2017; Kuchler et al., 2023) and numerous studies based on surveys or lab experiments provide evidence in support of the extrapolative expectations (e.g., Case et al., 2012; Greenwood and Shleifer, 2014; Piazzesi and Schneider, 2009).[13] Recent research also highlights the role of expectations in explaining house price movements during the 2000s housing boom-bust cycle (e.g., Duca et al., 2021; Glaeser and Nathanson, 2017; Kuchler et al., 2023; among many others).

While the assumption of extrapolative expectations seems well founded, there are some skeptics about its relevance for the time-varying persistence on a couple of grounds. First, the causal inference between expectations and persistence of house price growth is not straightforward because extrapolative expectations can be the consequence of persistent movement of housing prices. Second, expectations may be less relevant for house price persistence in the presence of constraints in income or credit supply, which limits buyers' ability to realize their expectations regarding house price movements. In addition, the availability of credible measures of expectations is another thorny issue. Researchers often use survey elicitation to measure expectations (e.g., Kuchler et al., 2023), but surveys regarding future expectations are limited to certain geographic areas and specific timeframes. Alternatively, past house price growth is commonly utilized in empirical research as a non-survey measure of housing market expectations, due to its backward-looking nature. Duca et al. (2021), for example, advocate using annualized house price appreciation over the preceding *four years* as a proxy for such backward-looking expectations, a measure also adopted in our empirical analyses below.[14]

Shifts in credit conditions are also often regarded as an important driver of the housing boom of the 2000s. The premise is that the increased availability of mortgage credit substantially boosted housing

[12] See Howard and Liebersohn (2022) and references therein for the recent debate on the roles of expectations versus credit in the recent boom and the bust. In general, the two factors can interact with each other and are therefore hard to disentangle, but geographic analyses can provide testable implications of these competing explanations as discussed below.

[13] Survey evidence, for instance, often suggests that investors typically expect higher future returns after a protracted rise in prices (Case and Shiller, 1989; Case et al., 2012; Greenwood and Shleifer, 2014; Piazzesi and Schneider, 2009).

[14] More recent literature offers additional non-survey measures of housing market expectations, such as the sentiment based on news media (Soo, 2018). Unfortunately, these measures are unavailable at the geographic units under study. The reader is referred to Kuchler et al. (2023) for a comprehensive survey on housing market expectations.

demand, consequently driving up house prices and contributing to heightened persistence (Favara and Imbs, 2015; Favilukis et al., 2017; Mian and Sufi, 2009). In their comparison of the influences of credit supply and extrapolative expectations, Griffin et al. (2021) maintain that the surge in housing demand during the boom-bust cycle of the 2000s is primarily attributed to the credit supply channel, rather than the extrapolative expectations channel.

Nevertheless, measuring exogenous shifts in credit supply can be challenging for empirical analyses, as it is often intertwined with other variables like housing speculation. Moreover, there is a lack of consensus on the sources behind credit supply expansion. While some studies have linked the increase in credit supply and the subsequent housing boom to the widespread use of mortgage securitizations (e.g., Loutskina and Strahan, 2009; Mian and Sufi, 2009,2022), others have emphasized the role of banking deregulations in the housing boom of the 2000s (e.g., Favara and Imbs, 2015). Considering that borrowing capacity is contingent on credit availability, banking integration through banking deregulations might have played an important role in expanding credit supply and influencing changes in house price dynamics. Indeed, Favara and Imbs (2015) show that banks' ability to open branches across state borders had significant impacts on the housing boom in the 2000s, primarily through large expansion of credit.[15] In the current study, we utilize proxy measures of credit supply related to banking integration, using data on bank deposits.

3 The data

The data for this study were collected from a variety of publicly accessible sources. Specifically, we obtained *quarterly* Housing Price Indices (All-Transactions Indexes) for the US national, nine Census divisions, and a large number of MSAs from the FHFA. The FHFA HPI represents a weighted average of price changes in single-family residential properties, financed through conforming loans, and sold or refinanced multiple times. Compared to the Case-Shiller Index, the FHFA HPI offers several advantages, including longer available data observations for a larger number of MSAs (see Choi and Hansz, 2021). The raw HPI data were acquired from the FHFA website (*https://www.fhfa.gov*) and subjected to seasonal adjustment using the Census Bureau's X-13 ARIMA routine. This allows us to calculate the seasonally-adjusted quarterly house price growth on a quarter-over-quarter basis.

For the city-level data, our final sample comprises quarterly data for 279 metropolitan areas spanning from 1980.Q1 to 2021.Q3 ($T = 167$, $N = 279$). Our extensive dataset, which covers several

[15] Banking deregulations contributed to the expansion of mortgage credit supply in two main ways: firstly, by enabling banks to broaden their deposit collection and lending capabilities by establishing branches across state lines, and secondly, by loosening lending standards due to heightened competition in local lending markets (e.g., Choi and Hansz, 2021).

boom-and-bust cycles in the U.S. housing market, is essential for providing reliable inferences regarding time-varying behavior of house price growth.[16]

From the pool of more than 300 MSAs available throughout the sample period, the selection of MSAs was based on the data's availability for the key variables used in our empirical analyses. The sample's broad geographic coverage is noteworthy as it encompasses over 80% of the total U.S. population during the study period. Figure 2 shows a map of the 279 MSAs included in our study, with larger circles indicating greater increases in the persistence of house price growth after 1997, measured by SARC estimates.[17] The choice of 1997 as the demarcation point was guided by the visual evidence presented in Figure 1. It is worth noting that numerous MSAs exhibiting large increases in persistence are located in states within the Midwest and South regions.

To gain further insights into the persistence changes over time and across cities, Figure 3 plots the level of persistence (measured by SARC estimates) before and after 1997 for the 279 MSAs in our dataset. As depicted in Figure 3, persistence seems to have increased after 1997 in most MSAs. Furthermore, a more significant increase in persistence is evident in MSAs that were previously characterized by lower levels of persistence, particularly in the Southern states, in line with the visual observations from Figure 2.

Other MSA-level variables utilized in this study are sourced from various publicly-available datasets. Per capita bank deposits are obtained from the Summary of Deposit (SOD) data, available at the FDIC website (*http://www7.fdic.gov/sod/*). The SOD dataset provides annual observations (as of June 30 of each year) on all deposit-insured commercial banks and savings associations, regarding the ownership, location, and deposits of each U.S. bank branch from 1994 onwards. Data for per capita income and population density are taken from the Bureau of Economic Analysis (BEA) regional accounts, with annual availability for each MSA in the sample. Unemployment rate data are collected from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS) program.

For the measure of housing supply constraints, we utilize the Wharton Residential Land Use Regulation Index (WRLURI), originally constructed by Gyourko et al. (2008) and later updated by Gyourko et al. (2021). This index provides a comprehensive overview of various aspects of the local regulatory framework pertaining to housing supply at the MSA level, with higher index values indicating a more restrictive regulatory environment (see Appendix B).

[16] During the postwar period, there were three notable boom-bust cycles in U.S. house prices. The first postwar housing boom occurred during the Great Inflation of the 1970s, followed by a second boom in the early 2000s, and the third was spurred by the COVID-19 pandemic (Kuchler et al., 2023).

[17] The SARC is estimated using the Hansen's (1999) 'grid bootstrap' based median-unbiased (MUB) estimator. See Appendix A for a further discussion on the SARC.

4 Time-varying parameter autoregressive (TVP-SV-AR) model

While Figures 1 through 3 present persuasive evidence of time variation in the persistence of both national and urban house price growth, further formal analysis would be beneficial to validate this observation. Research in macroeconomics has shown that models with time-varying parameters (TVP) are able to parsimoniously capture dynamic behavior of important macroeconomic variables like inflation (e.g., Aastveit et al., 2023; Nakajima et al., 2011; Primiceri, 2005).[18] In particular, the time-varying parameter vector autoregressive (TVP-VAR) model, originally introduced by Primiceri (2005), has gained popularity thanks to its flexibility and robustness in capturing the time-varying properties of data.

Inspired by previous efforts, this study utilizes a time-varying parameter autoregressive model with stochastic volatility (hereafter, TVP-SV-AR model) to estimate the time variation in house price growth persistence.[19] The TVP-SV-AR model is suited for our purpose on a couple of grounds. First, given the close relationship between business cycle and housing cycle, as outlined by Leamer (2007), the TVP model is a reasonable choice for capturing possible nonlinearities in house price growth. Second, house price growth, closely related to the primary component of the U.S. CPI (the user cost of owner-occupied shelter), is conceptually linked to inflation rates, whose dynamic behavior aligns well with TVP models.

Importantly, we incorporate stochastic volatility (SV) into TVP models not only to enhance estimation accuracy, but also to avoid model misspecifications (e.g., Nakajima, 2011). Combining the TVP-AR model with stochastic volatility (SV) enables us to effectively track time variation in both persistence and volatility simultaneously in a flexible and robust manner. Because the TVP model without the SV term, which assumes constant volatility, tends to produce biased estimates in the presence of volatility variation in disturbances (Cogley and Sargent, 2005; Primiceri, 2005), it is essential to incorporate time variation in both parameters and volatility simultaneously to prevent erroneous inference (Chan, 2018; Lubik and Matthes, 2015). The TVP-SV-AR model also has the capability to account for the nonlinearities stemming from structural economic shifts and heteroskedastic shocks, which are commonly observed in housing markets.[20]

[18] Aastveit et al. (2023) provides comprehensive discussion regarding the stability of parameters in macroeconomic variables.

[19] We focus on the TVP-SV-AR model instead of the TVP-SV-VAR model, because our ultimate interest is to estimate the persistence of house price growth within the framework of an AR model.

[20] Previous studies have shown that nonlinear approaches such as Markov Switching models can effectively capture key aspects of house price dynamics (e.g., Ang and Timmermann, 2013; Guirguis et al., 2005). However, Primiceri (2005) suggests that the TVP model can better capture shifts in aggregated private sector behavior compared to Markov

In the current study, we consider the following TVP-SV-AR model,

$$y_t = \alpha_t + \rho_t y_{t-1} + \sum_{k=1}^{p-1} \zeta_{k,t} \Delta y_{t-k} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2), \tag{1}$$

where y_t represents the house price growth in time t and σ_t^2 denotes the time-varying variance of housing price disturbances. All parameters in eq.(1) are time varying such that $\Lambda_t = \{\alpha_t, \rho_t, \zeta_{1,t}, ..., \zeta_{p-1,t}\}'$. Among them, the key parameter of interest, ρ_t, represents the SARC at time t and captures the time-varying persistence of house price growth.[21] Following Primiceri (2005), the vector of coefficients (Λ_t) is assumed to evolve as random-walks, with associated disturbances that are jointly normally distributed and mutually and serially uncorrelated.[22] Specifically,

$$\Lambda_{t+1} = \Lambda_t + u_t, \qquad u_t \sim N(0, \Sigma). \tag{2}$$

This parsimonious specification allows persistence to have both permanent and purely transitory components (see Primiceri, 2005). The model can also capture numerous patterns without introducing additional parameters that need to be estimated (Lubik and Matthes, 2015).

Following Nakajima (2011), it is assumed that the variance of ε_t evolves according to $\sigma_t^2 = \gamma exp(h_t)$ where the law of motion for h_t is given by,

$$h_{t+1} = \phi h_t + \eta_t, \qquad \eta_t \sim N(0, \sigma_\eta^2). \tag{3}$$

In addition to the independent noise component, η_t, the SV model can capture the time variation of the log variance of disturbances, where past volatility of house price growth can affect the current volatility of house price growth.[23] As a result, the volatility of house price growth in the TVP-SV-AR model can stem either from changes in the transmission mechanism, captured by the mean equation's time-varying parameters, or from the impact of the exogenous shock η_t in eq.(3) (Primiceri, 2005).[24]

Switching models.

[21] The optimal lag length ($p-1$) is selected by the BIC rule with the maximum lag length set as eight.

[22] Recent findings from Aastveit et al. (2023) support the use of random-walk assumptions to characterize the dynamics of both house and stock prices. However, Aastveit and Anundsen (2022) find an asymmetric response of urban house prices to monetary policy shocks. Given that house price persistence is influenced by factors beyond monetary policy shocks, we believe the random-walk specification can effectively capture the dynamics of house price movements.

[23] In the literature, volatility of house price growth, which is unobservable by nature, has often been characterized by conditional variance models such as the GARCH models (see Ghyles et al., 2013). While GARCH models explicitly constrain volatility to only be a function of past observations of the residuals of house price growth, SV approach relates the variance to an independent stochastic component that can allow volatility of house price growth to be impacted by news arrival. For this reason, SV is preferred (see Chan and Grant, 2016).

[24] A thorny issue in this regard is that TVP-SV-AR model is likely to attribute time variation in the data to the SV term rather than to the lag coefficients. However, this is of less concern in our case because we found that the variations in house price growth are driven primarily by variations in the lag coefficients rather than by the SV.

While theoretically it might be possible to estimate the TVP-SV model with conventional tools based on a state-space representation, the computational burden for evaluating the likelihood function poses a significant challenge. This is especially true given the large number of MSAs that we evaluate. We therefore rely on Bayesian inference and the use of the Markov Chain Monte Carlo (MCMC) algorithm with a Gibbs sampler.[25]

Against this backdrop, we estimate the *univariate* TVP-SV-AR model using the national house price growth in eq.(1).[26] The results, based on 1,000 posterior draws, are displayed in Figure 4 and illustrate several points. First, all the estimated coefficients exhibit significant variations over time, in particular the coefficient of interest, ρ_t. As shown in Figure 4, the SARC estimate ($\hat{\rho}_t$) fluctuated around the value of 0.3 before the mid-1990s when it jumped to around 0.8 in the early 2000s, similar to the visual evidence noted in Figure 1. This indicates a large time variation in the persistence of national house price growth. Moreover, the notable increase in persistence occurred even before the housing market boom in the 2000s, implying that the rise in persistence was likely driven by other factors than the housing market boom itself.

Similar time-varying patterns are witnessed in other coefficient estimates. As illustrated in the upper panel of Figure 5, the volatility of national house price growth remained relatively stable until the mid-1990s, after which it began to rise, reaching its peak in the early 2000s before reverting to pre-mid-1990s levels. This indicates that SV of national house price growth exhibits a hump-shaped profile around the early 2000s, potentially reflecting structural changes in the U.S. housing market prompted by shocks during that period. Interestingly, the time varying volatility captured by the SV term, as depicted in Figure 5, is not as pronounced as the time variation in persistence depicted in Figure 4. This suggests that the dynamics of national house price growth might have been driven by time-varying persistence, possibly due to systematic policy changes or shifts in private sector behavior, rather than by the time-varying volatility of non-policy-related shocks. The lower panel of Figure 5 plots the evolution of intercept term ($\hat{\alpha}_t$) along with the associated one-standard deviation intervals. $\hat{\alpha}_t$ appears to move counter to the direction of house price growth, declining during the housing boom and rising during the subsequent housing market downturn.

[25] The basic idea underlying the MCMC approach is that computational methods can be used to obtain moments from the desired posterior distribution by repeatedly sampling a Markov chain. The algorithm used in the Gibbs sampling takes into account the correction to the ordering of steps suggested by Del Negro and Primiceri (2015). To compute the posterior estimates, we use an initial burn-in of 100 and subsequently draw an additional 1,000 samples. The reader is referred to Nakajima (2011) and Lubik and Matthes (2015) for further details on the implementation of the TVP-SV-AR model.

[26] Throughout the paper, we estimate the SARC using the univariate TVP-SV-AR model due to the complexity of interpreting the persistence in multivariate models, where the system eigenvalues will vary depending on the included variables.

5 Factors behind the time-varying persistence

The results of our TVP-SV-AR model analysis in the preceding section confirm the substantial variation in the persistence of U.S. house price growth across different periods. It is equally important to comprehend the factors behind the temporal variation of the persistence. Given that national house price is the aggregation of a number of sub-national house prices, and that large persistence in aggregate house price growth can result from a wide variety of disaggregated house prices (e.g., Choi et al., 2006), geographical considerations may provide insight into the factors conducive to the time-varying persistence.

In this section, we explore the factors behind the temporal variation in house price growth persistence by analyzing geographically disaggregated data. According to the spatial equilibrium model (e.g., Rosen-Roback model), spatial heterogeneity is inherent in house prices, as they are influenced by local factors such as wages, amenities, and housing supply conditions specific to each area. Consequently, the housing literature consistently highlights the significant variability in house price dynamics across different geographic regions (Case and Shiller, 1989; Ferreira and Gyourko, 2012; Gyourko and Voith, 1992). Recent research, as partially listed in Table 2, has extensively investigated this issue at a disaggregated level, uncovering significant geographic heterogeneity in the persistence of house price growth. Because the geographic heterogeneity in persistence may arise from a variety of factors, including demand-side factors as well as housing supply conditions (Capozza et al., 2004; Duca et al., 2021; Glaeser et al., 2008; Gyourko et al., 2008; Oikarinen et al., 2018; Saiz, 2010), disaggregated data analyses can shed light on the underlying factors by relating geographically heterogeneous patterns in the persistence of house price growth to a range of candidate drivers under scrutiny.

In this regard, we leverage a wider variation in house price growth persistence observed in urban house price growth (e.g., Oikarinen et al., 2018). Specifically, we estimate the time-varying persistence of urban house price growth in the univariate TVP-SV-AR model in eq.(1), and then link the persistence estimates to the measures of credit supply, extrapolative expectations, and other control variables within the framework of panel data regression.

5.1 Panel data regression analyses with city-level data

We utilize city-level house price data for 279 U.S. MSAs ($N = 279$) over the period 1994-2020 ($T = 27$).[27] Our analysis here comprises two sequential stages in a similar spirit with Gorodnichenko and

[27] Because some key explanatory variables like bank deposits are only available annually for the period after 1994, we utilize annual data for the panel data analysis. Consequently, the city-level persistence estimates ($\hat{\rho}_{it}$) are annualized by

Talavera (2017).[28] At first, we estimate the persistence of house price growth individually for each of the 279 MSAs using the univariate TVP-SV-AR model in eq.(1). Next, we regress the estimated city-level persistence ($\hat{\rho}_{it}$) onto city-level characteristics associated with the credit supply and expectations channels and other control variable, within the framework of panel data regression models. To this end, we utilize two popular panel data techniques suitable for our panel dataset: the two-way fixed effects (TWFE) model and the Common Correlated Effects (CCE) estimation method introduced by Pesaran (2006).

We conduct our analysis using the following standard panel data model:

$$\hat{\rho}_{it} = \mu_i + \beta_1 CS_{it} + \beta_2 EXP_{it} + W_{it}'\varphi + v_{it}, \tag{4}$$

where $v_{it} = \delta_t + \epsilon_{it}$ (TWFE) or $v_{it} = \boldsymbol{\gamma}_i'\mathbf{f}_t + \epsilon_{it}$ (CCE). The dependent variable ($\hat{\rho}_{it}$) is the SARC estimates of house price growth in city i for year t, obtained from the TVP-SV-AR model in eq.(1). Figure 6 plots $\hat{\rho}_{it}$ across 279 MSAs (on the right scale) spanning from 1994 to 2020 (on the left scale). The figure shows significant variations in the persistence of urban house price growth, not only over time but also across MSAs.

Before proceeding, it is worth mentioning that the dependent variable is an 'estimated' variable, and therefore it is subject to sampling uncertainty. Let $\hat{\rho}_{it} = \rho_{it} + \omega_{it}$, where ω_{it} is the estimation error. Substituting this expression in (4), we obtain

$$\rho_{it} = \mu_i + \beta_1 CS_{it} + \beta_2 EXP_{it} + W_{it}'\varphi + v_{it}^*,$$

where $v_{it}^* = v_{it} - \omega_{it}$ is composed of the original error, v_{it}, and the estimation error (ω_{it}). Hence the correlation between the estimation error ω_{it} and our regressor variables will be key for panel estimation of β_1 and β_2. We assume $E\left(\omega_{it} | EXP, CS\right) = 0$, in which case the consistency and asymptotic normality results of TWFE and CCE estimators continue to apply, and ω_{it} only affects the panel estimates by contributing to larger standard errors (i.e. larger sampling uncertainty of $\hat{\beta}_1$ and $\hat{\beta}_2$), which also can be consistently estimated.

In eq.(4), the main explanatory variables of interest are CS_{it} and EXP_{it}, which respectively represent credit supply and extrapolative expectations in city i for year t. The city-level credit supply (CS_{it}) is proxied by the *per capita deposit growth* in city i for year t, which is regarded as a reliable indicator of credit supply because deposit availability is a crucial source of credit provision (e.g.,

averaging over four quarters.

[28] In their two-step approach, Gorodnichenko and Talavera (2017, Section III) first estimate the speed at which online prices adjust in the U.S. and Canada. They then incorporate this estimated speed into a subsequent regression analysis. A similar two-step approach is also used by Chudik, et al. (2021).

Aguirregabiria et al., 2020; Becker, 2007).[29] Given the importance of banking integration in credit supply expansion, cities with stronger links through the national banking system are likely to have a higher level of credit supply. For the city-level extrapolative expectations (EXP_{it}), we use the *previous four-year average house price growth* as a proxy following much of the literature (e.g., Duca et al., 2021). By comparing the significance of the coefficients of these two variables, we can assess their relevance in explaining the time-varying persistence of urban house price growth. Intuitively, one may expect MSAs with faster growth either in credit provision or in extrapolative expectations to experience a larger increase in persistence. So, positive signs are expected for the coefficients estimates, or $\beta_1 > 0$ and $\beta_2 > 0$.

W_{it} is a set of time-varying MSA-level control variables, encompassing per capita income growth, population density growth, and unemployment rate in city i for year t. By incorporating time-varying city characteristics (W_{it}) as controls, we aim to mitigate potential biases related to omitted variables. Population density is linked to transaction volumes in housing markets, thereby influencing information costs (e.g., Capozza et al., 2004). Unemployment rate is included to control for frictions in the labor market, which can affect housing demand through labor force migration. Higher unemployment rates may also decrease house prices and transaction volume by deteriorating matching quality. Additionally, we control for time-varying housing supply constraints at the city level by utilizing the MSA-level Land Unavailability (LU) measure developed by Lutz and Sand (2023).[30] The error term v_{it} therefore captures unobservable changes in other drivers of house price growth persistence.

Eq.(4) is estimated using two panel data approaches: the two-way fixed effects (TWFE) estimation and the Common Correlated Effects (CCE) estimation. In panel data analysis, it is important to take into account cross-sectional dependence, as emphasized by Oikarinen et al. (2018). Cross-sectional relationships among cities may naturally exist due to factors such as mobility and trade (e.g., Choi et al., 2020) and multi-market bank networks (e.g., Choi and Hansz, 2021), resulting in possibly strong correlations in urban house price growth across cities. The two panel data techniques considered here differ in dealing with the cross-sectional dependence: unobserved common time-effects for the TWFE

[29] We are well aware that loans, not deposits, are more closely related to credit supply. Nevertheless, we use deposits as a proxy measure of credit supply not just because banks typically originate loans funded with deposits, but also because the availability of local deposits is closely related to loan supply as many banks make loans in the same region where deposits are collected (e.g., Aguirregabiria et al. 2020). This is particularly the case for relatively small sized banks without a branch network. Using the fraction of seniors as an instrument for the local supply of deposits and of bank loans, Becker (2007) finds that local deposit supply affects the local banking sector and local economy significantly.

[30] Extending the Saiz (2010) land availability measures to finer levels of geography, Lutz and Sand (2023) have constructed the LU as the share of undevelopable land at the MSA level. Unlike most other measures of housing supply constraints, the LU measure is varying not only across geographic units (MSAs) but also over time, for 720 counties between 2002 and 2022. See Appendix B for more discussions on the LU index.

model and unobserved common factors with heterogenous loadings (or interactive effects) in the CCE approach. The CCE approach is more general and more robust compared with TWFE. In fact, the CCE estimation approach of Pesaran (2006) have become so popular that it has given rise to a separate CCE literature, which generalizes the original modeling assumptions of Pesaran (2006) in a numbes of directions (see Westerlund and Kaddoura, 2022, and references cited therein for recent methodological contributions). We report both CCE mean group (CCEMG) and CCE pooled (CCEP) estimators for our analyses.

Table 3 presents the results from our panel data regression analyses. Not surprisingly, there is a discrepancy in the outcomes between the TWFE and CCE estimators, primarily due to their differing methods of handling the inherent cross-sectional dependence in the panel data (Han et al., 2022). The two explanatory variables of interest, CS and EXP, exhibit differences in terms of their signs and significance depending on the panel method used. In the TWFE model, both CS and EXP show an anticipated positive sign, but neither is statistically significant. In contrast, in the CCE estimation, the coefficient estimate of extrapolative expectations (EXP) consistently lacks significance and exhibits mixed signs, whereas the coefficient estimate of credit supply (CS) is positive and significant. We base our inference on the CCE estimators since the CRT test of Han et al. (2022), presented at the bottom of Table 3, indicates that the CCE estimators are preferred over the TWFE model for our data, as evidenced by the test statistic (117.70) exceeding the 5% critical value of 14.31. For the control variables (W_{it}), our panel data analyses reveal mixed results. While the impact of per capita income growth is consistently positive and significant in all cases considered, the coefficients on population density growth and unemployment rate are statistically insignificant.

A broadly similar story is told in the lower panel of Table 3 in which the city-level Land Unavailability (LU) is added to control for time-varying housing supply constraints. Interestingly, the estimated coefficient for housing supply constraints is consistently positive and statistically significant, regardless of the panel methods employed. This finding corroborates previous research suggesting more persistent movements of house prices in more supply-constrained cities (e.g., Capozza et al., 2004; Lai and Van Order, 2017; Oikarinen et al., 2018).

To sum, our panel data regression results favor the credit supply channel over the extrapolative expectations channel in explaining the observed time-varying persistence in urban house price data. While backward-looking extrapolative expectations may still play a role in house price growth persistence, our data suggest that the time varying persistence is more closely associated with the credit supply channel. This conclusion aligns with previous studies that highlight shifts in credit conditions as a major driver of house price movements (e.g., Favara and Imbs, 2015; Favilukis et al., 2017; Griffin et al., 2021; Mian and Sufi, 2022, among others).

5.2 Endogeneity concerns and an IV analysis

Our analyses in the preceding section suggest that the time-varying persistence of house price growth is better explained by the credit supply channel. While intriguing, identifying the causal effects of credit supply expansion is challenging due to possible endogeneity concerns. One source of endogeneity is the possibility of omitted variables that correlate with both credit supply and house price growth persistence, or, $Cov(CS_{it}, \epsilon_{it}) \neq 0$ in eq.(4).

While we can alleviate the omitted variable issue to some extent by augmenting time-varying control variables in our regression and allowing unobserved common factors to correlate with regressors in the CCE approach, it is still possible that omitted variables could simultaneously drive credit supply and house price persistence. Another endogeneity issue is reverse causality, where persistence of house price growth can affect credit supply if persistent increases in house prices (and hence collateral values) induces more credit availability and provision (e.g., Gelain and Lansing, 2014).

To address this endogeneity issue, we follow much of the literature and utilize an instrumental variable (IV) approach for credit supply. Identifying valid and strong instruments is by no means straightforward, but we construct the following local Bartik (1991) type shift-share as an instrument for local credit supply (e.g., Borusyak et al., 2022)[31],

$$D_{it} = \delta_{i,t} \cdot \Delta Dep^{US}_{-i,t}, \tag{5}$$

where $\delta_{i,t}$ represents the local share of deposit in city i at time t, and $\Delta Dep^{US}_{-i,t}$ denotes the national deposit growth at time t excluding the city i. Notice that the national deposit growth is computed as leave-one-out measures to avoid mechanical correlation between the national trend estimate and city i credit supply (Borusyak et al., 2022). As a result, D_{it} can be viewed as the city-level Bartik-type "shift-share" instruments for local credit supply, or shift-share shocks exploiting exogenous local credit supply changes that combine local deposit share ($\delta_{i,t}$) with national deposit growth ($\Delta Dep^{US}_{-i,t}$).

Table 4 presents the IV regression results using the city-level Bartik instruments (D_{it}) for credit supply in the panel data regressions in eq.(4). The results are qualitatively similar to those reported in Table 3. The impact of credit supply is consistently positive and significant in all cases considered,

[31] The basic intuition behind Bartik (1991)-type instrument is to project national data onto local regions to ensure the exogeneity of the instrument. In the related literature, shift-share measures have been extensively used as instruments for local house prices based on local exposure to exogenous national productivity trends (e.g., Mian et al., 2013; Saiz, 2010).

but mixed outcomes for extrapolative expectations. This confirms the robustness of our results to the use of instruments for endogeneity.

5.3 The role of housing supply constraints

Our focus so far has been placed on how factors related to the housing demand contribute to the variations in persistence over time. However, recent studies on housing supply have emphasized the importance of regulatory constraints and associated costs in explaining fluctuations in house prices (e.g., Aastveit et al., 2020; Capozza et al., 2004; Glaeser et al., 2008; Huang and Tang, 2012). Moreover, evidence is emerging that the impact of housing demand factors on persistence is contingent upon the availability of housing supply in local markets (e.g., Aastveit et al., 2023; Duca et al., 2021; Lai and Van Order, 2017; Oikarinen et al., 2018). Due to regulatory constraints and geographical limitations, for instance, the ability of the housing supply to respond to changes in demand is restricted, thereby increasing the persistence of house prices (e.g., Huang and Tang, 2012).[32] For this reason, it is worth investigating whether the impact of credit supply and extrapolative expectations on house price growth persistence depends on housing supply constraints. It is intuitive to anticipate a stronger effect of housing demand factors in cities with more stringent housing supply constraints.

To investigate this, we employ a measure of housing supply constraints at the city level. The measure we utilize is the Wharton Residential Land Use Regulation Index (WRLURI), which offers a summary measure of the stringency of the local regulatory environment regarding permitting, zoning, and entitlement processes. This index, originally developed by Gyourko et al. (2008) and later updated by Gyourko et al. (2021), takes on a larger value for a more restrictive regulatory environment regarding housing supply. Previous studies have often utilized this index to show that cities with heavier regulations on the housing market tend to experience faster and more volatile movements of house prices (e.g., Choi and Hansz, 2021; Gyourko et al. 2008).[33]

We begin by utilizing the CCEMG estimation outcomes from the preceding section to investigate the connection between the marginal effects of credit supply and expectations, and the degree of housing supply constraints across 279 MSAs. A positive relationship is anticipated if the influence of credit supply or future price expectations is stronger on the persistence of house price growth in

[32] Huang and Tang (2012) document that more restrictive housing supply constraints are linked to larger responses of housing prices to economic shocks, leading to greater house price persistence. Aastveit et al. (2020) also highlight the differences in housing supply elasticities as an important contributor to the wide cross-city disparities in the movements of U.S. house prices.

[33] Although not reported here to conserve space, our results are largely similar using alternative popular measures of housing supply constraints, such as the land unavailability measure of Saiz (2010) and the inverse of the housing supply elasticity by Guren et al. (2021).

cities with more stringent housing supply constraints. As depicted in Figure 7, there appears to be no clear correlation between the WRLURI and the marginal impact of credit supply (on the left panel) and expectations (on the right panel), as evidenced by the nearly horizontal fitted lines. In other words, the influence of credit supply or expectations on persistence may not necessarily be stronger in cities with more stringent housing supply constraints. This finding corroborates the recent research by Howard and Liebersohn (2023) indicating that housing supply elasticity alone does not account for much of the variation in house price appreciation, particularly in less regulated regions. It also aligns with our earlier observation that regions with relatively lax housing supply constraints, such as the Midwest and South, experienced a more notable increase in persistence.

Additionally, we run the following TWFE regression,

$$\hat{\rho}_{it} = \alpha(D_{it} \times WRLURI_i) + W_{it}'\Psi + \mu_i + z_t + \varepsilon_{it}, \tag{6}$$

where D_{it} denotes the city-level exogenous credit supply shock defined in eq.(5) and $WRLURI_i$ represents the measure of housing supply constraint in city i. The other variables remain the same as in eq.(4). The interactive term $(D_{it} \times WRLURI_i)$ captures whether or not the response of persistence to local credit supply shock varies with the degree of local housing supply constraints. Given the well-established positive effect of housing supply constraints on house price growth persistence (e.g., Aastveit et al., 2023), a positive sign is anticipated for the coefficient α. Table 5 presents the regression results in which we find no significance of the interactive term $(D_{it} \times WRLURI_i)$, i.e., the response of persistence to local credit supply does not hinge on the local housing supply constraints.

Taken together, there is no compelling evidence that the impact of credit supply or expectations on house price growth persistence is stronger in cities with stricter housing supply constraints. Our findings, however, do not refute the positive impact of housing supply constraints on the persistence of house price growth *per se* (e.g., Lai and Van Order, 2017; Oikarinen et al., 2018), as presented in the lower panel of Table 3. Instead, our results imply that the positive impact of credit supply or extrapolative expectations on house price growth persistence may operate through the mechanisms other than housing supply constraints.

6 Concluding remarks

The persistence of house price growth has been a salient feature of the U.S. housing markets. Despite its significant implications on critical aspects of the economy, such as household consumption and the labor market, little has been understood about the stability of this persistence over time, let alone the factors driving it. Understanding how and why house price growth persistence varies over time is of great importance due to the significant role housing markets play in key aspects of the economy. Policymakers, for instance, could benefit from detailed insights into the factors influencing the time variation in persistence. Large geographic disparities in the persistence of house price growth indicate that one-size-fits-all monetary policy will have heterogeneous effects across different regions in the U.S.

The current study adopts a novel approach to estimating the time-varying persistence of house price growth. Utilizing a TVP-SV-AR model, we have uncovered compelling evidence of time-varying persistence in both national and urban house price growth in the U.S., especially notable after the mid-1990s. The observed time-varying persistence hinges on geographic location, with regions previously characterized by lower persistence showing a more significant variation over time. This phenomenon is hard to explain solely based on conventional housing demand fundamentals or housing supply factors, suggesting the presence of additional factors influencing the patterns of time-varying persistence.

To examine the factors influencing time-varying persistence, we focused on the role of two primary housing demand factors identified in recent literature as potential drivers of house price fluctuations: credit supply and extrapolative expectations. By connecting the geographical differences in estimated persistence across MSAs to observable city-level characteristics using panel data regressions, we found that credit supply, rather than expectations, provides a better explanation for the time-varying behavior of persistence. The elevated persistence of urban house price growth, especially in areas with limited capital in the Midwest and South, can be attributed to the expansion of credit supply facilitated by interstate banking integration and securitizations. The persistence of house price growth is also positively associated with the stringency of housing supply constraints, as widely documented in the literature. However, the influence of credit supply on persistence is not dependent on the severity of housing supply constraints. Importantly, our findings remain robust even after addressing endogeneity concerns using suitable instruments.

While our study provides novel insights into the U.S. housing markets, it also emphasizes the necessity for further exploration in future research. To gain deeper insights into persistence dynamics, it would be beneficial to explore the time-varying behavior throughout future housing cycles. Moreover, based on city-level aggregate house price data, our study does not offer detailed evidence at a more granular level. Conducting comprehensive analyses with more granular data is crucial to mitigate potential aggregation bias. Additionally, exploring additional sources of geographic heterogeneity in the time variation of persistence beyond the two housing demand factors examined here holds promise. Nevertheless, our study concludes that house price growth persistence is far from stable.

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Table 1: Diverse sources of persistence of house price growth in the literature

Information costs	Frictions in demand	Supply costs and constraints
Asymmetric information	Business cycle	Housing market regulations
High transaction costs	**Credit constraints**	Long lag of construction
Non-standardized and heterogeneous properties	**Extrapolative expectations**	Construction costs
Illiquidity	Investors' sentiment	Geographic constraints
Search/gradual learning		

Table 2: Summary of selected previous studies on the persistence of urban HP growth

Study	Data	Methodology	Driving force and notable findings
Beracha and Skiba (2011)	380 U.S. MSAs during 1983-2008	AR model & Dynamic panel GMM	Overconfidence of buyers. Stronger momentum in the West region and during 2004-2008.
Capozza et al. (2004)	62 U.S. MSAs during 1979-1995	Error correction model (ECM)	Information & supply costs. Higher serial correlation in areas with higher incomes, population growth and real construction costs
Griffin et al. (2021)	3725 U.S. zip code areas during 2003-2006	One-way fixed effect (FE) models	Housing market boom-bust in the 2000s is better explained by credit supply than extrapolative expectations
Gu (2002)	Quarterly CMHPI for U.S. states during 1975-1999	Moving average model and variance ratio test	Trading strategies of buyers & sellers. Marked difference in autocorrelation across locations and over time
Guren (2018)	MLS listing data during 2008-2013	IV analysis	Momentum is amplified by strategic complementarity of sellers
Gyourko and Voith (1992)	56 U.S. MSAs during 1971-1989	Two-way fixed effects model	No mention on driving force. Unequal persistence across MSAs
Lai and Van Order (2017)	45 U.S. MSAs during 1980-2012	Pooled Mean Group & Mean Group estimation	Stronger momentum in cities with lower housing supply elasticities
Oikarinen et al. (2018)	70 U.S. MSAs during 1980-2015	Two-stage regression with Pooled OLS & FMOLS regressions	Geographic differences in the momentum depends on housing supply elasticity
Plazzi et al. (2010)	53 U.S. MSAs during 1994-2003	GMM estimation	Commercial real estate returns are persistent and time-varying
Schindler (2013)	20 U.S. MSAs during 1987-2009	Autocorrelation & variance ratio tests	Transaction costs. Geographic heterogeneity in momentum
Sinai (2012)	249 U.S. MSAs during 1980-2010	Basic statistics	Non-fundamental factors. Heterogeneity in serial correlation
Titman et al. (2014)	97 U.S. MSAs during 1980-2011	Dynamic panel regression	Demand persistence & supply rigidities. Heterogeneity in the serial correlation

Table 3: Results of panel data regression (279 MSAs over 1994-2020)

Explanatory variables	TWFE	CCEP	CCEMG
(A) Model 1: for 279 MSAs over 1994-2020			
CS (deposit growth)	0.022 [0.016]	0.056* [0.033]	0.260‡[0.068]
EXP (previous 4-yr HP growth)	0.026 [1.738]	-1.254 [3.290]	-6.409 [5.434]
Per capita income growth	0.220†[0.107]	0.295‡[0.134]	0.464†[0.211]
Population density growth	0.056 [0.049]	-0.018 [0.216]	5.465‡[1.118]
Unemployment rate	0.008 [0.006]	0.007 [0.007]	0.001 [0.008]
Observations	7,074	7,074	7,074
CRT test	Test-statistics: 117.70 Critical value: 14.31		
(B) Model 2: for 261 MSAs over 2002-2020			
CS (deposit growth)	0.013 [0.013]	0.058‡[0.024]	0.178* [0.105]
EXP (previous 4-yr HP growth)	-2.292 [1.709]	-6.769 [4.157]	-9.684 [7.870]
Per capita income growth	0.025 [0.108]	0.161 [0.102]	0.100 [0.268]
Population density growth	0.053 [0.043]	0.527†[0.256]	3.809‡[1.456]
Unemployment rate	0.009 [0.006]	-0.001 [0.007]	-0.010 [0.011]
Land Unavailability (LU)	0.171‡[0.044]	0.166†[0.077]	0.230* [0.122]
Observations	4,959	4,959	4,959
CRT test	Test-statistics: 29.87 Critical value: 14.30		

Notes: The regression equation is eq.(4), namely

$$\hat{\rho}_{it} = \mu_i + \beta_1 CS_{it} + \beta_2 EXP_{it} + W_{it}'\varphi + v_{it},$$

where the dependent variable is the time-varying persistence measure ($\hat{\rho}_{it}$) of MSA-level house price growth estimated in the TVP-SV-AR model. CS_{it} denotes the bank deposit growth as a proxy for credit supply measure, and EXP_{it} represents the previous four-year house price growth as a proxy for the housing market expectations (Duca et al., 2021). W_{it} is a vector of housing demand fundamentals, including per capita income, population density, and the unemployment rate, as well as the housing supply factor (LU) in Model 2. The total number of observations is 7,074 for 279 MSAs during 1994-2020 for Model 1 and 4,959 observations for 261 MSAs over 2002-2020. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5%, and 10% significance levels with the corresponding clustered s.e. inside square brackets.

Table 4: IV regression results using city-level Bartik instrument

Explanatory variables	TWFE	CCEP	CCEMG
CS (deposit growth)	0.311‡[0.028]	0.102‡[0.009]	0.086‡[0.007]
EXP (previous 4-yr HP growth)	6.324‡[1.342]	-1.253 [2.787]	-10.066‡[4.108]
Per capita income growth	0.440†[0.086]	0.280‡[0.121]	0.424†[0.151]
Population density growth	0.043 [0.030]	-0.038 [0.146]	3.611‡[0.931]
Unemployment rate	0.017‡[0.004]	0.007 [0.006]	-0.002 [0.007]

Notes: The regression equation is

$$\hat{\rho}_{it} = \mu_i + \beta_1 \widehat{CS}_{it} + \beta_2 EXP_{it} + W_{it}'\varphi + v_{it},$$

where $\widehat{CS}_{it}$ is the predicted values of CS_{it} estimated from $CS_{it} = \mu_i + \eta_1 D_{it} + \eta_2 EXP_{it} + W_{it}'\varphi + v_{it}$ where D_{it} is the city-level Bartik instruments constructed by $D_{it} = \sum \delta_{i,t_0} \cdot \Delta Dep_{-i,t}^{US}$. All the other variables are the same as in the footnote of Table 3.

Table 5: The role of housing supply constraints

Explanatory variables	TWFE	CCEP	CCEMG
$D_{it}\times$ WRLURI	0.012 [0.014]	0.463 [0.298]	-3.686 [3.316]
Per capita income growth	0.222†[0.108]	0.281†[0.134]	0.379* [0.134]
Population density growth	0.035 [0.045]	-0.035 [0.164]	0.410‡[0.102]
Unemployment rate	0.008 [0.006]	0.007 [0.007]	-0.006 [0.008]

Notes: The regression equation is

$$\hat{\rho}_{it} = \alpha(D_{it} \times WRLURI_i) + W_{it}'\Psi + \mu_i + z_t + \varepsilon_{it},$$

where D_{it} is the city-level Bartik shift-share shock for the exogenous credit supply shock, constructed by $D_{it} = \sum \delta_{i,t_0} \cdot \Delta Dep_{-i,t}^{US}$. $WRLURI_i$ is the measure of housing supply constraint in city i. All the other variables are the same as in the footnote of Table 3.

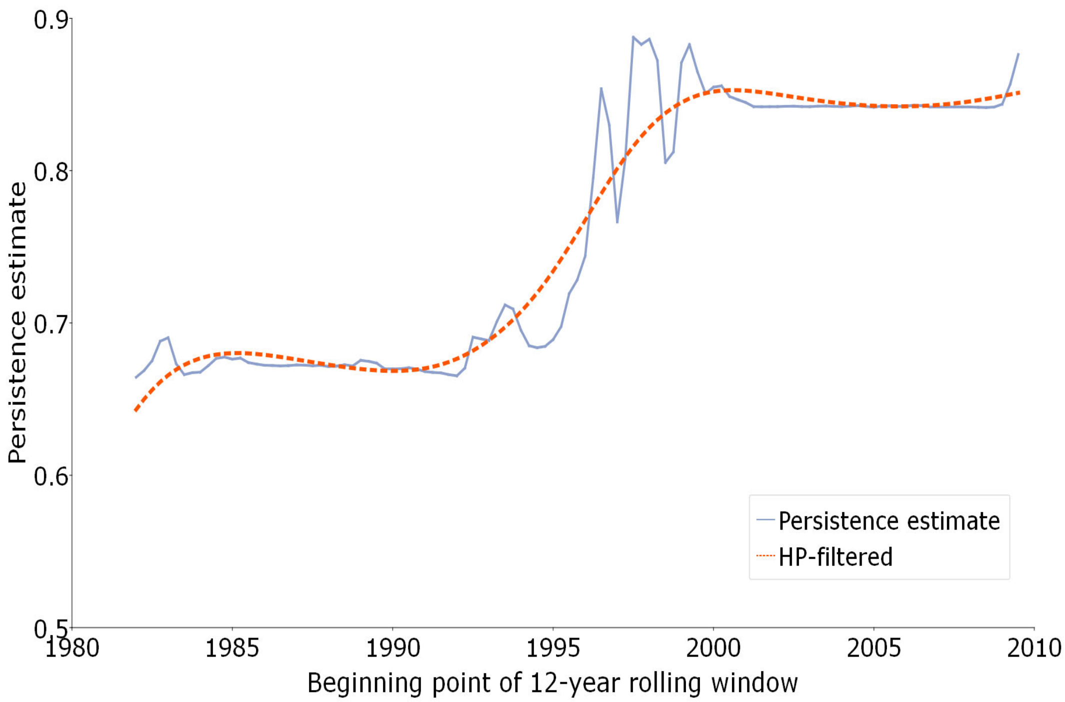


Figure 1: Evolution of the SARC estimates for national house price growth using 12-year rolling windows

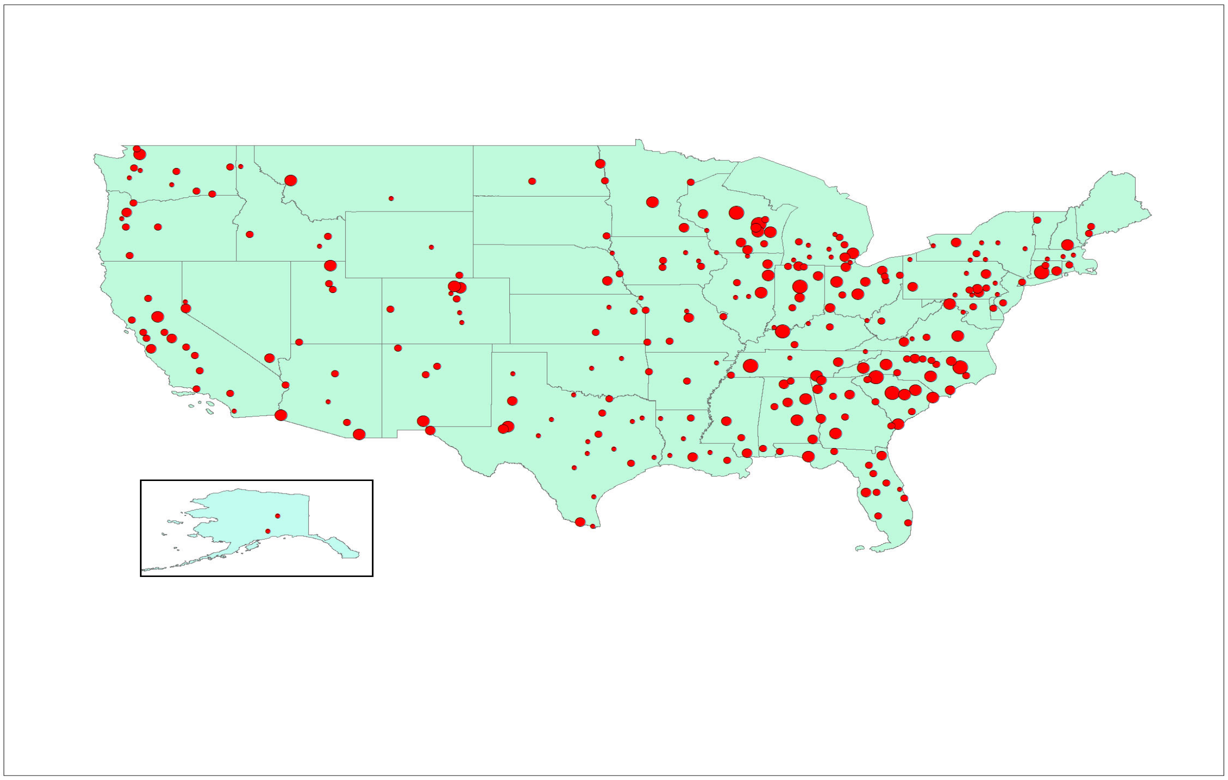


Figure 2: Map of 279 MSAs based on the persistence change after 1997

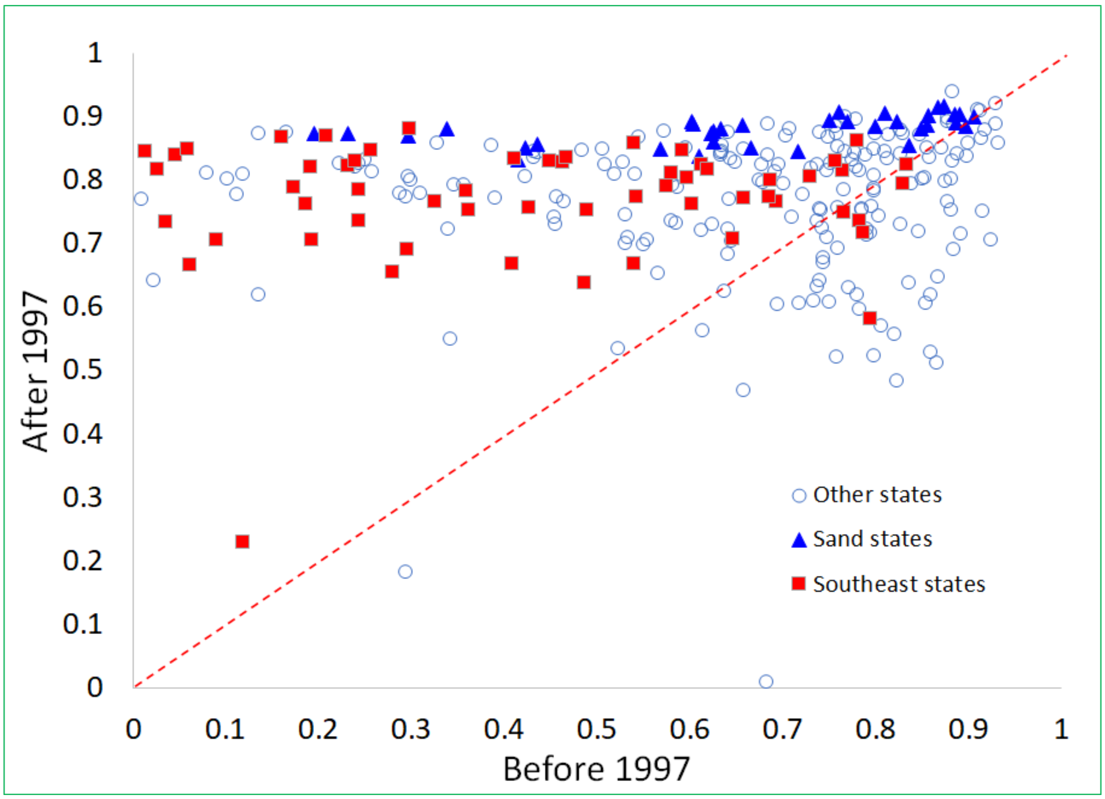


Figure 3: Change in persistence of MSA house price growth before and after 1997

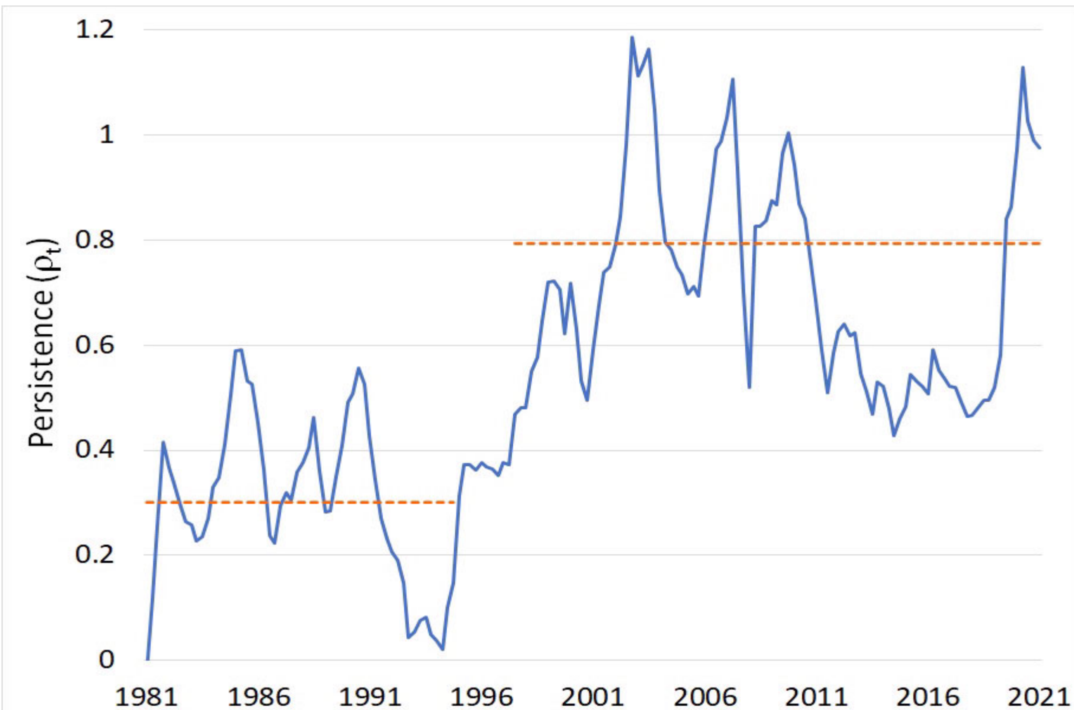
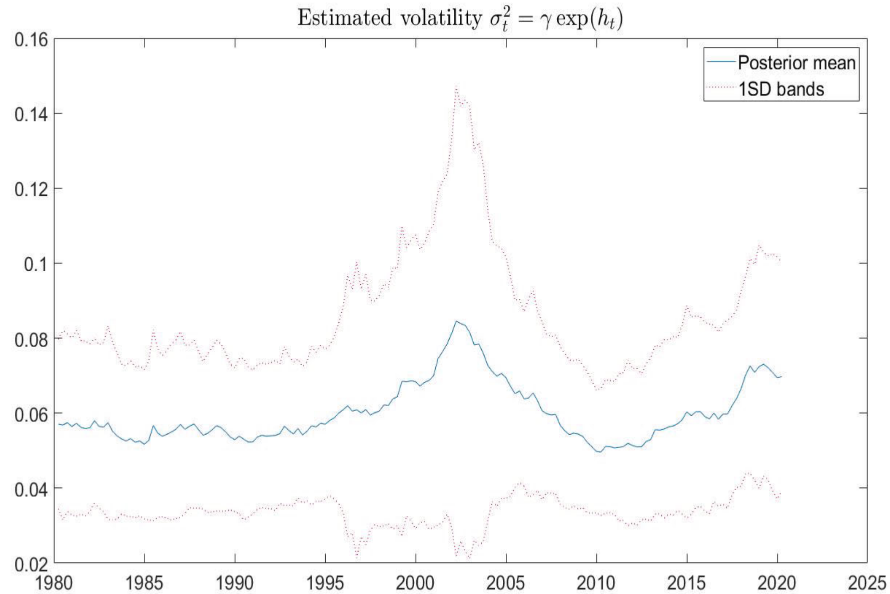
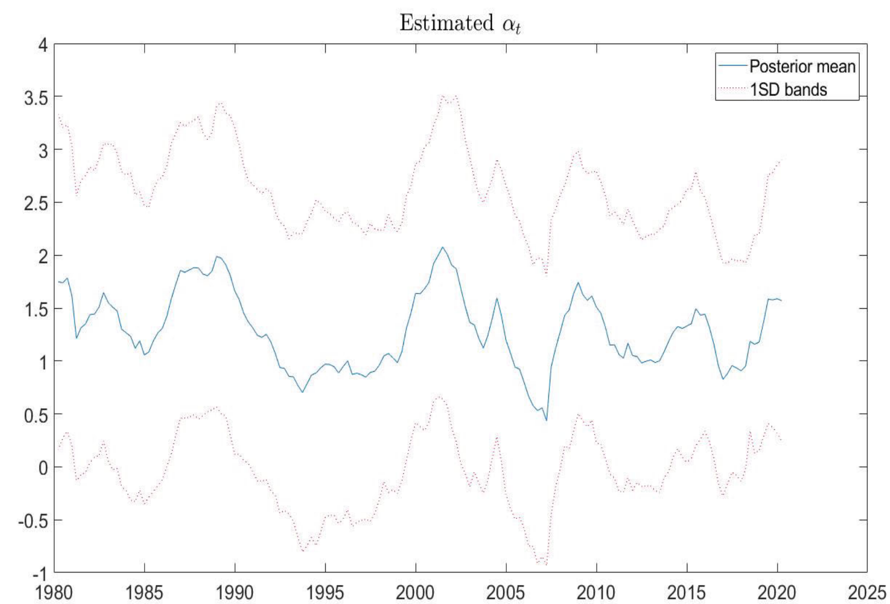


Figure 4: Time-varying SAR coefficient estimated in TVP-SV-AR model for the U.S. house price growth



(a) Posterior estimates for stochastic volatility of national house price growth



(b) Posterior estimates for intercept term (α_t) for national house price growth

Figure 5: Posterior estimates of stochastic volatility (top) and intercept term (bottom) estimated in TVP-SV-AR model for national house price growth

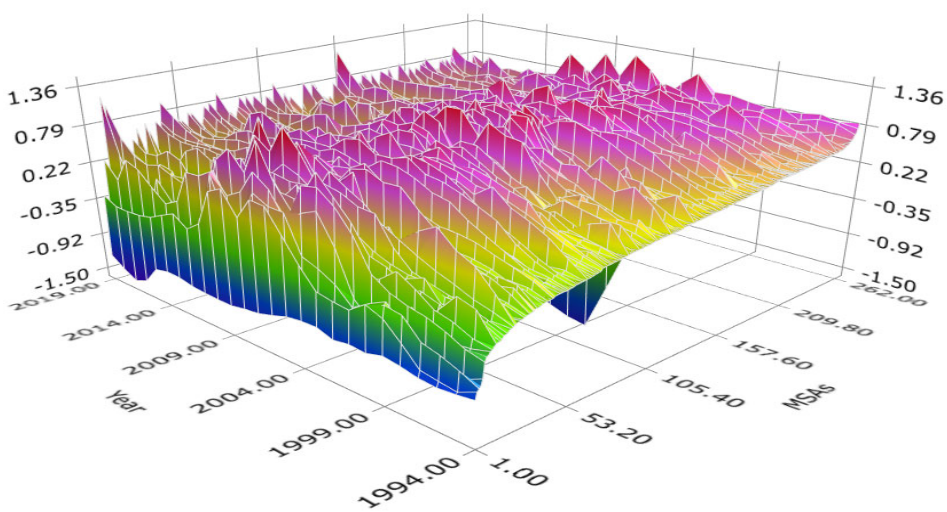


Figure 6: Time-varying persistence estimated from TVP-SV-AR model across 262 MSAs over 1994-2020

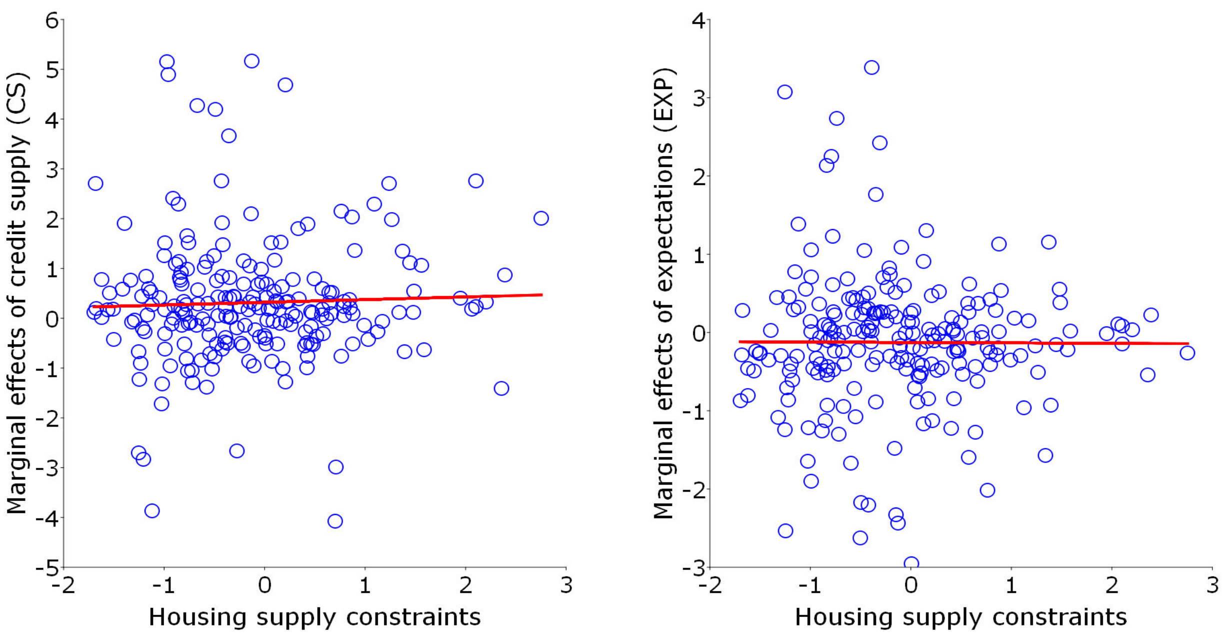


Figure 7: Relationship between housing supply constraint measures (on the horizontal axis) and marginal effects of housing demand factors on persistence (on the vertical axis)

Appendix: Data Description

Appendix A: Sum of autoregressive coefficients (SARC) in AR model

A number of approaches have been employed to assess the extent of the persistence in house price growth. One such approach is to use univariate time series model based on the autocorrelation properties of house price growth. A standard practice of measuring the magnitude of persistence is to estimate the persistence within the framework of an autogressive (AR) model. We measure the persistence of each housing price growth rate using the sum of autoregressive coefficients (SARC) in the AR(p) representation of

$$\begin{aligned} y_t &= \alpha + \sum_{j=1}^{p} \beta_j y_{t-j} + \varepsilon_t \\ &= \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t \\ &= \alpha + \rho y_{t-1} + \sum_{k=1}^{p-1} \zeta_k \Delta y_{t-k} + \varepsilon_t, \end{aligned}$$

where y_t represents the growth rate of house price at time t and $\zeta_k = -\sum_{j=k+1}^{p} \beta_j$. As such, $\rho = \sum_{j=1}^{p} \beta_j$ denotes the SARC. The lag length (p) is selected using BIC with a maximum lag length of 12. Compared to relatively complex multivariate models in which economic variables other than past values of house price growth are used as conditioning variables (e.g., Plazzi et al., 2010), univariate models have the advantage of being robust to the data quality and better forecasting performance. To deal with the well-known downward small sample bias embedded in the OLS estimation of ρ (Choi et al., 2006), we follow the common practice in previous studies (e.g. Choi and O'Sullivan, 2013) and employ the Hansen's (1999) 'grid bootstrap' based median-unbiased (MUB) estimator. Persistence is higher for a larger value of SARC (ρ).

Appendix B: Measures of housing supply constraints

The Wharton Residential Land Use Regulation Index (WRLURI), developed by Gyourko et al. (2008) and subsequently updated by Gyourko et al. (2021), is a popularly used measure of the stringency of local housing regulations. It comprises eleven sub-indexes that provide a summary of various aspects of the regulatory environment. A low value of the WRLURI index indicates a less restrictive or more permissive approach to regulating the local housing market. A large body of research (e.g., Choi and Hansz, 2021; Gyourko et al. 2008) has shown that cities with more stringent housing regulations, and hence lower elasticity of housing supply, experience faster and more volatile growth in house price. As such, the WRLURI index provides a valuable tool for measuring the stringency of local housing regulations and their impact on the dynamics of house prices in different cities. Our results are largely similar using alternative popular measures of housing supply constraints, such as the land unavailability measure of Saiz (2010) and the inverse of the housing supply elasticity by Guren et al. (2021).

Another measure of housing supply constraints considered in the current study is the Land Unavailability (LU) developed by Lutz and Sand (2023, *https://github.com/ChandlerLutz/LandUnavailabilityData*). The basic idea of the LU measure is that the amount of land available for development plays a crucial role in local housing supply elasticity. While other measures of housing supply constraints, such as the WRLURI, solely capture cross-sectional variation, the LU measure varies not only across geographic units but also over time. Specifically, it spans 720 counties from 2002 to 2022 and 1,828 counties from 2011 to 2022, making it suitable for our panel data regression analysis as presented in Table 3. As noted by Conklin et al. (2022), the LU index is highly correlted with the Saiz's (2010) measure.

Appendix C: Comparison between the TWFE model and the CCE estimation

The basic idea of the TWFE model is to estimate the marginal effect of the explanatory variables of interest, while taking into account city-level heterogeneity (μ_i) and common macroeconomic shocks (δ_t). The MSA-fixed effects (μ_i) control for potentially confounding omitted variables, including locational differences in economic growth, housing supply elasticity, and demographic trends. The year-fixed effects (δ_t) control for year-specific unobserved confounders that are common to all cities, such as macroeconomic shocks. The inclusion of year-fixed effects is particularly important because house prices may comove in different cities due to national house price trends, such as changes in mortgage rates or credit supply changes. By controlling for these national trends, the TWFE model permits us to isolate the effects of the variables of interest on persistence.

The TWFE model, however, assumes that the error terms (ϵ_{it}) in eq.(4) are uncorrelated with the explanatory variables, which may not hold if unobserved common factors exist that cause non-zero correlations between explanatory variables and error terms. Moreover, if common nationwide shocks, such as monetary policy shocks, affect all MSAs to varying degrees, the year-fixed effects (δ_t) in the TWFE model may not be able to capture the heterogeneous effects of common shocks (Han et al., 2022; Sul, 2019). To address this issue, Pesaran (2006) proposes the use of Common Correlated Effects (CCE) estimators. The basic idea behind CCE estimators is to control for unobserved common factors by augmenting the model with cross-sectional averages of the dependent variable as well as explanatory variables. CCE estimation is known to be robust to different types of cross-sectional dependence in the error term, possible unit roots in factors, and slope heterogeneity.