Understanding Geographic Comovement of House Prices among U.S. Cities: The Role of Financial Integration

Chi-Young Choi*
University of Texas at Arlington

October 8, 2019

Abstract

Large and persistent difference across metro areas has been a salient feature of the house price movements in the U.S. The current study uncovers another prominent feature. Regional house price movements became a lot more synchronized after the early 2000s when the comovement of house prices surged drastically. We find that the comovement surge can be explained to a great extent by financial integration following regulatory changes in the banking industry. Utilizing novel measures of city-pair level financial integration based on bank deposit data, we find that financial integration has a significant positive effect on the inter-city HP comovement through nationally operating banks. Bilateral financial integration through national banking system, however, has strengthened the linkages of local housing markets mainly by connecting cities that were formerly segmented financially and physically farther apart. Our key findings are robust to various sample variations and alternative measures of comovement.

Keywords: House price, Comovement, U.S. cities, Financial integration, Banking deregulation.

JEL Classification Numbers: G10,G12,R12,R21,R31

*E-mail: cychoi@uta.edu. The author has benefited from helpful comments from Knut Aastveit, John Adams, Enrique Martinez-Garcia, Meng Li, Ivan Paya, David Rakowski, Sriram Villupuram, Mike Ward, and the participants at the 2019 AREUEA International Conference at Bocconi University in Milan, Italy, the 53rd Annual Conference of the Canadian Economic Association (CEA) in Banff, Canada, the 27th Annual Symposium of the Studies of Nonlinear Dynamics and Econometrics (SNDE) at the FRB Dallas, and the COB Incubator seminar at UTA. Any errors or omissions are the responsibility of the author's.

1 Introduction

Geographic segmentation has been a prominent feature of the U.S. housing markets. A wealth of empirical evidence suggests that house prices (HP, henceforth) in the U.S. differ considerably across locations, and the geographic difference in HPs has persisted over time (e.g., Gyourko et al. 2013, Van Nieuerburgh and Weill 2010). To get a better sense of this, we plot in the top panel of Figure 1 the geographic dispersion of HPs among 302 U.S. MSAs since 1975, measured by the coefficient of variation (CV) of single-family home prices.[1] The inter-city dispersion of HPs exhibits a clear upward trend over time, indicative of a growing divergence of local HPs across U.S. metro areas. A similar picture is painted in the bottom panel of Figure 1 where the log of average HPs of MSAs are plotted for the previous five years against the following five years over the past four decades. The strong positive association observed in the scatterplot suggests persistent disparities of HPs across cities, i.e., high-priced areas have stayed high-priced and low-priced places have stayed low-priced.

The story, however, changes somewhat significantly when it comes to the growth rates of HP. Figure 2 plots the cross-city correlation of HP growth rates for 5-year rolling window at several levels: mean, median, and the interquartile range (25^{th}- and 75^{th}-percentiles) among 302 MSAs. Simple visual inspection of Figure 2 reveals that HP growths in the U.S. exhibit only moderate, and sometimes negative, correlations among the urban areas prior to 2000, implying a lack of comovement in the metro HPs before 2000. Around the early 2000s, however, there was a sudden and large jump in the cross-city correlation, suggesting a sharp rise in the comovement of local HPs.[2] The average cross-city correlation of HP growths, for example, has sharply increased from less than 0.2 in the 1980s and 1990s, to above 0.8 in the early 2000s. A similar pattern is witnessed even in the 25^{th}-percentile of the cross-city correlation, which increased substantively from below zero before the early 2000s to above 0.7 afterwards.[3] The sharp increase even in the 25^{th}-percentile suggests that the comovement surge was significant across all metro areas. At first glance, one may wonder whether the surged comovement of HP growths can be reconciled with the growing cross-city divergence of HPs found earlier. The two findings, however, are not necessarily contradictory because HPs can still diverge over time even when their growth rates are similar, so long as the original HPs were dissimilar across locations. Interestingly, the timing of the comovement surge appears to correspond to the beginning of 2001-2006 housing market boom, which is known to have been triggered by an expansion in the

[1] As explained in more detail in Section 2, we construct city-level HPs by combining the Federal Housing Finance Agency (FHFA) quarterly HP indexes with MSA retail HPs from the Council for Community and Economic Research (C2ER) for the period 1975.Q1-2017.Q3.

[2] The literature offers two types of spatial interactions: comovements and interdependence. While comovement generally refers to a 'contemporaneous' spatial correlation across markets, spatial interdependence is more inclusive by referring to the presence of 'lagged' spatial correlation and comovement. Throughout the paper, we focus on the comovement while leaving the interdependence for future research.

[3] Although not reported here to economize on space, a similar comovement surge was observed at the state level and in other urban HP datasets such as the CoreLogic data.

credit supply of mortgage markets.

The primary purpose of this study is to delve into the comovement shift of urban HPs in the U.S. and tease out the key drivers behind it. For concreteness, our study is centered on two core questions: (1) what drove such a large and sudden increase in the comovement of HPs around the early 2000s; and (2) what are their qualitative and quantitative effects on the comovement shift. We attempt to address these questions by exploiting a broad dataset of single home prices of 239 U.S. MSAs for the period 1975-2017. The comovement jump observed in local HPs is interesting and important on a couple of grounds. First, given that integration of financial markets is often characterized by cross-location correlations in asset returns, the elevated comovement of local HPs may reflect a tighter linkage among regional housing markets in the U.S. This in turn leads to a greater chance of propagation of regional shocks to national economy (e.g., Kallberg et al. 2014, Pasquariello 2007). Recall that local HPs in the U.S. exhibit only moderate, and sometimes negative, correlations across locations prior to 2000. This weak or virtually no comovements of HPs across MSAs implies that HP changes were driven mainly by local idiosyncratic factors before 2000. By contrast, the increased comovement of HPs after 2000s indicates that local housing markets are influenced to a greater extent by national factors that commonly affect all regions in the nation. In this context, it is not surprising to see that regional housing boom-bust cycles in the 1980s and early 1990s predominantly affected the regions where they occurred (e.g., California and the Northeast), while more recent subprime mortgage crisis was spread quickly to the entire nation. Second, the increased comovement among U.S. regional housing markets may pose a serious challenge on the geographic portfolio diversifications (e.g., Zhu et al. 2013). Given that the benefits to geographic diversification among regional markets hinge on the degree of the comovement of local HPs, the increased comovement of regional HPs implies a reduced opportunity of geographic risk-sharing across local housing markets.[4] Taken together, a better understanding of the comovement of local HPs is crucial for both market participants and policymakers, in particular with the increasingly close relationship between housing markets and broader capital markets in the U.S. (e.g., Case and Shiller 1996).

Our study builds and extends on the previous literature in terms of data coverage and empirical methodologies. As reported in Table 1, the current study is not the first to report increased comovement of the regional HP growths. Some recent studies (e.g., Cotter et al. 2015, Hirata et al. 2012, Kallberg et al. 2014, Landier et al. 2017, see the summary in Table 1) document that HP movements in the U.S. became more synchronized recently. Landier et al. (2017) and Kallberg et al. (2014), for example, show that U.S. housing markets became highly synchronized across states and selected MSAs during 1990s. The authors, however, find only a mild and gradual rise of comovement over

[4] The lack of comovement before 2000, by contrast, apparently provided an opportunity for investors to diversify their exposure to regional housing market risks through geographically dispersed mortgage loans.

time, instead of a drastic surge as found here.[5] To the best of our knowledge, our study is the first to report such a sudden shift in the comovement of HPs. Moreover, whereas Landier et al. (2017) study the comovement of HPs among 50 U.S. states for the period 1976-2000 and Kallberg et al. (2014) did so only for 14 U.S. metropolitan areas during 1992-2008, our dataset covers a larger cross-section dimension (239 U.S. MSAs) over a much longer time horizon (1975-2017). In light of the nontrivial heterogeneity found in the regional housing markets in the U.S., analysis at a finer scale of disaggregation with a wider geographic coverage certainly adds value to addressing the central questions at hand, especially in identifying the factors behind the comovement jump.[6] Since housing markets are typically characterized by local factors like local income and populations, as well as other localized characteristics that may potentially impede interactions among regional housing markets, movements of HP are often believed to be closely linked to local economic fundamentals especially in the past two decades when the U.S. housing market has undergone drastic changes with a significant boom and bust (e.g., Ferreira and Gyourko 2014, Kallberg et al. 2014, Van Niewuerburgh and Weill 2010). While intriguing, local fundamental factors do not seem to be well aligned with the sudden jump observed in our data. If local HPs are driven by local factors, then it becomes challenging to explain such a drastic increase in the comovement across all metro areas. Besides, there is growing evidence in the literature that asset prices move together for reasons that are seemingly unrelated to fundamentals (e.g., Barberis et al. 2005, DeFusco et al. 2018).

One potential underlying mechanism that could account for the comovement surge is the role of financial integration across regions following interstate banking deregulations. It is widely documented in the literature that banking deregulations enhanced the regional financial integration that consequently imparted significant positive influences on the comovement of economic activities across regions (e.g., Goetz and Gozzi 2019). Interestingly, in terms of the point of timing, the increased comovement of HPs appears to coincide with similar developments in the financial sectors across cities after deregulations in the banking industry. Recent theoretical contributions (e.g., Morgan et al. 2004) highlight financial markets and institutions as an important element in the cross-region transmission of shocks. Banks operating in multiple locations are particularly important for understanding the geographical integration of economic activities as they promote the transmission of economic shocks across geographic areas through internal capital mobility. Empirical studies in this direction also have found that financial integration across regional economies imparted significant impetus to the movement of HPs in the U.S. (e.g., Landier et al. 2017, Loutskina and Strahan 2015, Michalski and Ors

[5] Landier et al. (2017) note that correlations of state-level house price growth have risen steadily over the sample period 1976-2000 and Kallberg et al. (2014) find a moderate rise of the city-level house price correlation.

[6] Compared to several nationwide housing cycles since the mid-1970s, for instance, there have been numerous city-level cycles with significant house price fluctuations. This large variation in HP movements across MSAs is useful for disentangling the key drivers, while controlling for conventional housing market demand and supply factors.

2012, Peek and Rosengren 2000).[7] A key empirical challenge in this regard is the lack of proper measure of financial integration is available at the city-level. To overcome this challenge, we construct a couple of novel proxy measures of city-level financial integration based on bank deposit data collected from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD): (i) deposit share of out-of-state banks; and (ii) co-Herfindahl index of banking market.

Applying the surrogate measures of city-level financial integration to the data, we find that financial integration following banking deregulations has played an important role in explaining the increased comovement of local HP growths. Our empirical results show that financial integration is positively associated with the comovement of HP growths, but negatively correlated with the change in the comovement of HP growth after 2000. That is, financial integration increases bilateral HP comovement, i.e., local HPs tend to move together between the cities that are financially more connected through banks operating in multiple regional markets. However, the effect of financial integration on the HP comovement change after 2000 is larger in the city-pairs that are financially more segmented previously. To rephrase, financial integration is in general conducive to more synchronous movements of local HPs, but not necessarily to a greater increase in the comovement after 2000 when interstate banking deregulations were fully fledged. We find that the comovement surge in local HP growths took place after 2000 mainly in the city-pairs that were formerly more segmented economically, financially, and geographically farther apart. City-pairs that were more integrated each other economically and financially before 2000 did not experience much increase in the comovement of HPs after 2000. This can be interpreted as saying that financial integration following banking deregulation must have strengthened the linkages of local housing markets primarily by linking markets that were formerly less connected to the rest of the nation. We confirm the robustnees of our findings to the use of an alternative measures of correlation, alternative breakpoints and sample periods, as well as the exclusion of some outliers in the data.

The remainder of this paper is structured as follows. The next section describes the data employed in the current study and documents a descriptive analysis of the data. Section 3 provides further evidence on the comovement of HP growths based on more formal empirical analysis. In Section 4, we focus on the role of financial integration in explaining the movements of local HPs after discussing how to construct two proxy measures of city-level financial integration. Section 5 carries out pair-wise regression analyses to make quantitative assessments of the explanatory power of financial integration for the comovement surge. Section 6 concludes the paper. The Appendix contains a detailed descrip-

[7] Much of the recent literature stresses that policy or regulatory changes on financial markets can be exogenous to the evolution of local HP growth because policy changes are unilateral (e.g., Favara and Imbs 2015). Using bank branching deregulation in the 1990s, for instance, Favara and Imbs (2015) claim that the direction of causality typically runs from an expansion in credit supply to HPs, with a larger HP increase in the states where there was deregulation. Relatedly, Goetz and Gozzi (2019) study the effect of bilateral banking integration across U.S. states on the comovement of economic activity between states.

tion of the data used in the current study and discusses the explanatory variables employed in the regression analysis.

2 The data and preliminary analysis

Our analysis draws on the data from a number of sources. Our main dataset consists of the MSA-level HP index (HPI) from the Federal Housing Finance Agency (FHFA), which are quarterly single-family home prices available from 1975 for most MSAs in the U.S.[8] Constructed from data on repeated sales price of homes, the FHFA HPI has a particular appeal as it alleviates the composition biases arising from quality changes by controlling for the size or quality of the house. Furthermore, since it is the single home all-transactions index that includes both sales and refinancings, it is less vulnerable to the selectivity bias arising from cyclical variation in the composition and frequency of home sales. Another important advantage of this dataset relative to other sources of city-level HPs, including the Case-Shiller price index, is the coverage of a relatively long time for a large number of MSAs encompassing most of the U.S. population.[9]

With that said, the FHFA dataset is subject to some limitations. Since it is constructed from transactions data acquired through the GSEs, it only includes homes purchased with conforming mortgages securitized by the GSEs. This leaves out all the rest, such as sub-prime and other non-conforming mortgage loans, that were largely responsible for the fast growth of national HP in the mid-2000s (e.g., Mian and Sufi 2009). In consequence, our HPI data may understate the sensitivity of house prices to alternative credit, especially in the inelastic-supply areas.[10] Another drawback of the FHFA data is that it is in the index form normalized based on certain base year and hence cannot be used for a direct comparison of HPs across cities. To deal with this, we compute city-level HPs in dollar value by combining the FHFA indexes with the MSA retail HPs obtained from the Council for Community and Economic Research (C2ER) retail price survey dataset, Cost of Living Index (COLI). To be specific, we collect from the C2ER data the actual retail prices of house with the same specifications (new house for 2,400 sqft and 8,000 sqft lot with 4 bedrooms and 2 baths) as of the fourth quarter of 2000, and then construct city-level HPs by extending backward and forward by applying the house growth rates obtained from the FHFA indices.[11] This facilitates cross-MSA

[8] The raw HPI data are downloaded for the period 1975.Q1 to 2017.Q3 from the FHFA website ($https : //www.fhfa.gov/SupervisionRegulation/FannieMaeandFreddieMac$).

[9] The Case-Shiller home price indices, another popular HPI data set based on a repeat-sales methodology, is available only after 1987 for 20 MSAs. As shown by Paciorek (2013), however, the correlation between the two sets of HP indices is quite high, above 0.95 in most metropolitan areas.

[10] In addition, because the FHFA index is a weighted price index by averaging price changes in repeated sales or refinancing on the same properties that have been sold multiple times, it may have some measurement issues when the number of repeat transactions is small relative to total transactions. See Nagaraja et al. (2010, Chap.3) for further discussions on the limitations of the FHFA's HPI. As a robustness check to this issue, we consider an alternative HPI data (the CoreLogic dataset) and obtain qualitatively and quantitatively similar results.

[11] This is similar in spirit to the approach adopted by Paciorek (2013) who constructed dollar-valued measure of HP

comparisons not only in the dynamics of HP growth, but in the patterns of HPs *per se*. In spite of these limitations, our HP dataset seems to be arguably the best available to the public at the city level in terms of the data coverage.

Among the 302 MSAs where the FHFA HPI data are available for the entire sample period, we drop 63 MSAs for which the observations are unavailable for some covariates used in our regression analysis. This leaves us with 239 MSAs in the continental U.S. over the period 1975.Q1 to 2017.Q3 ($T = 171$), which cover more than 75 percent of the total U.S. population. It bears emphasis that we concentrate on nominal HP instead of real HP due to the limited availability of appropriate price data at the city level.[12] HP growth rates are computed for each MSA by the log quarterly differences in the FHFA home price index after seasonal adjustment. Our panel dataset is extensive in both time series and cross-sectional dimensions compared to those employed in the previous studies. As noted by Kose et al. (2003), however, the benefit from including more MSAs could be outweighed by the complication arising from over-representation by a large number of smaller MSAs even when major metropolitan areas have a disproportionate influence on the nation's housing market. In addition, our long time series data are susceptible to a number of structural changes in the economic relationships because they include several business cycles, such as the recent national housing boom and bust as well as the regional housing bubble of the 1980s (e.g, Del Negro and Otrok 2007, Luciani 2015).[13] Nevertheless, we stick to the long span data in the belief that they provide additional useful insights on the underlying mechanisms of HP dynamics. The longer time period is particularly appealing because the debate is far from settled on the underlying factors behind the changing dynamics of city-level housing prices. Also, given that our focus rests on the cross-city comovements of HP growth, a broad coverage of location is very helpful for gaining valuable new insights into the underlying mechanisms of HP movements by studying heterogeneity across a large number of cities. We revisit this issue in Section 4.3 when we examine the robustness of our findings to the variations in sample coverage.

Before proceeding, it is illuminating to check how well the MSAs included in our data represent the entire housing market conditions. To this end, we construct the (population-weighted) aggregation of HPs from the 239 MSAs in our dataset and plot it side-by-side against the S&P/Case-Shiller national HPI. As shown in Figure 3, we find a close fit between the two series, both on the level (top panel) and for the growth rates (bottom panel), with the correlation exceeding 90%. The bottom panel of

series by pegging the FHFA indices to the mean HP in each city from the 2000 Census.

[12] Due to the lack of adequate city-level CPIs for the entire MSAs under study, it is infeasible to construct MSA-level real HPs. BLS's urban CPI data are available only for a handful of cities and mostly after 1990. Usual practice of deflating by the national CPI serves no purpose here because of the considerable variations in the cost of living across locations. Moreover, deflating by inaccurate measures of local cost of living can be additional source of measurement error.

[13] For this reason, Del Negro and Otrok (2007) choose the first quarter of 1986 as the starting date partly because state-level HP index data are very noisy for many states before the mid-1980s, and because there were many institutional and structural changes in the housing finance sector in the early 1980s.

Figure 3 suggests that the Case-Shiller index exhibits a bit larger volatility in HP growth relative to the FHFA index, but the growth rates of the two HP indices are highly correlated (0.91) and the correlation is even higher (0.95) after 2000.

We also draw on a number of sources for additional data on local economic environment and local housing market conditions that are used for our regression analysis below. The data in this regard include per capita income, population, housing market constraints, bank deposits, and the latitude and longitude of cities. The data for these variables are obtained from a variety of sources presented in Table A.1 in Appendix A. We obtain the MSA level per capita personal income and population data from the Bureau of Economic Analysis (BEA). We collect the data of the supply-side frictions in local housing market from a couple of popular sources: the measure of local regulatory environment (the Wharton Residential Land Use Regulation Index, WRLURI) developed by Gyourko et al. (2008) and the elasticity of housing supply by Saiz (2010). They are downloaded from the authors' webpages. It is widely agreed that national shocks that commonly affect housing markets in all metropolitan areas have differential effects on city-level HPs due to the differences in these housing supply constraints. We rely on the FDIC dataset to measure the city-level financial integration. To be concrete, we use the Summary of Deposits (SOD) database from the FDIC at $http://www2.fdic.gov/sod/$, which provides the annual data (as of June 30 of each year) of all deposit-insured commercial banks on the ownership, location, and deposits of each bank branch in the U.S. from 1994 onward. Since the SOD tracks bank deposits at the branch level, it allows us to calculate the share of out-of-state bank deposit and the co-Herfindahl index as the proxy measures of city-level financial integration as further explained in Section 4.2. The reader is referred to Appendix B for further discussions on the control variables employed in our study.

Table 2 provides the summary statistics of major variables used in our analysis, for the full sample as well as two sub-samples splitting into the periods 1975-1999 and 2000-2017. The demarcation of sample period is largely based on the graphic evidence obtained from Figure 2. The table includes cross-city averages and dispersions measured by standard deviations and 90-10 percentile ratios for both the level and growth rates of the variables. In the full sample, the average HP among 239 MSAs is \$147,000, but with a fairly wide cross-city dispersion. The 90-10 percentile ratio is 1.79, indicating that the 90^{th}-percentile HP is almost twice as high as that of 10^{th}-percentile. It is worth noting that the average HP has risen substantially after 2000, from \$111,000 to \$212,700, and so did the intercity dispersion of HPs from 1.58 to 2.10. The average HP growth rates also vary a great deal across cities over the sample period. Nation's fastest-growing metro area (San Jose, CA) saw its HP increase at an average rate of 1.91 percent per quarter, about four times as fast as the slowest-growing metro area (Hickory, NC, 0.56 percent). Not only an enormous cross-city difference exists in the HP growth, but also the cross-city dispersion of HP growth rates has risen over time. The 90-10 percentile ratio of

HP growth rates almost doubled from 2.06 before 2000 to 4.00 after 2000. This is in stark contrast with the patterns from the intercity dispersion of the fundamental variables like per capita income and population. The 90-10 percentile ratio increased only mildly for the per capita income growth from 1.39 to 1.45 after 2000, and even decreased considerably for the population growth from 74.5 to 38.9. This result is not just consistent with the findings by earlier studies that income growth has been less dispersed than HP growth in the U.S., but also casts some doubts on the relevance of those fundamental variables in explaining the large shifts in the cross-city dispersion of HP growths observed after 2000.

3 Formal evidence of the comovement shift

Simple visual inspection of Figure 2 shows an obvious jump in the correlation of HP growths around the early 2000s. While the visual evidence is compelling, it may not be completely persuasive without further evidence based on more formal analysis. To substantiate our argument on the comovement surge, we analyze in this section the pattern and timing of the comovement shift in a more formal manner. The additional evidence presented here takes three forms. We first use the heteroskedasticity-adjusted correlation coefficients proposed by Forbes and Rigobon (2002) to ensure that the comovement shift is not an artifact of an increased volatility of HP growths. We also apply a formal test proposed by Morrison (1983) under the null hypothesis of no change in correlation before and after a specific time in the sample period. We then utilize an alternative measure of comovement based on a common factor model approach advocated by Cotter et al. (2015). This additional set of analyses is conducted for a various range of rolling windows to confirm that the timing of the surge is robust to the choice of rolling windows.

3.1 Heteroskedasticity-adjusted correlation coefficients

So far our evidence on the comovement shift is based on *unconditional* correlation estimate. As is well known in the literature (e.g., Chiang et al. 2007, Forbes and Rigobon 2002), however, unconditional correlation estimates are biased in case of variance shift because an increase in volatility is usually associated with an increase in correlation. For this reason, Forbes and Rigobon (2002) advocate the use of the following heteroskedasticity-adjusted correlation coefficients

$$\rho^* = \frac{\rho}{\sqrt{1 + \delta[1 - \rho^2]}}, \tag{1}$$

where ρ is the unadjusted (unconditional) correlation coefficient, $\delta = \frac{Var(r)_H}{Var(r)_L} - 1$, and $Var(r)_H$ and $Var(r)_L$ respectively denote the variance of HP growth (r) in high-volatility and low-volatility periods such that δ captures the relative increase in the variance of the high-volatility period.[14]

Since volatility tends to increase during financial crisis, it is possible that the correlation jump in HP growth could stem from a shift in variance during the Global Financial Crisis (GFC). To check whether or not the increase in correlation coefficients across metro areas is an artifact of high volatilities during financial crisis, we look at the heteroskedasticity-adjusted correlation for various rolling windows of 6-,8-,10-, and 12-years. Figure 4 plots the evolution of the heteroskedasticity-adjusted correlation over the sample period, with each line representing the statistics in eq.(1) for a specific rolling window. The numbers on the horizontal axis denote the middle point of each corresponding window. Take the upper-right panel (5-year window) for instance, 2000 on the horizontal axis captures the subsample period of 1998-2002, and so on. The results from four different rolling windows displayed in Figure 4 convey two important messages. First, we notice a jump in the heteroskedasticity-adjusted correlation in all cases considered. Second, our results seem to agree on the timing of comovement surge. They commonly show a large and sudden increase in the correlation at the approximately same time around the early 2000s, irrespective of the rolling windows considered. Because the comovement surge can be seen even after accounting for variance shift, it is likely that the comovement shift was driven by some other factors than the increased volatility during the recent financial crisis.

3.2 The standard Z-test for structural changes in correlation

Next, we utilize a formal testing tool proposed by Morrison (1983), called the standard Z-test, to formally test the comovement shift. Constructed under the null hypothesis of no change in correlation at a specific time (t), the standard Z-test statistic is given by

$$T = \frac{Z_0 - Z_1}{\sqrt{1/(N_0 - 3) + 1/(N_1 - 3)}} \sim N(0, 1), \tag{2}$$

where $Z_0 = 0.5ln[(1 + \rho_0)/(1 - \rho_0)]$ and $Z_1 = 0.5ln[(1 + \rho_1)/(1 - \rho_1)]$ are the Fisher transformations of the heteroskedasticity-adjusted correlation coefficients before (ρ_0) and after (ρ_1) t, and N_0 and N_1 denote the corresponding number of observations. The test statistic is approximately (standard) normally distributed and is known to be fairly robust to the non-normality of correlation coefficients. We apply this test to each city-pair of HP growth rates at the rolling windows of 6, 8, 10 and 12 years. In each rolling window, it follows that 28,441 ($= \frac{239 \times 238}{2}$) pair-wise correlation coefficients are calculated after correcting for the heteroskedasticity and tested. We then compute the fraction of all 28,441 city-pairs in our sample in which the null hypothesis of no change in correlation is rejected. Any significant change in the rejection rate therefore reflects a structural change in the comovement of HP growth rates.

[14] To address the heteroscedasticity problem, Chiang et al. (2007) use a multivariate GARCH model, which is also suitable for measuring time-varying conditional correlations. This approach, however, is of limited merit to our low frequency data in which the GARCH effect is not as strong as in the daily stock price data used by Chiang et al. (2007).

As illustrated in Figure 5, there is a notable jump in the rejection frequency around 2001-2 in all the rolling windows considered. The null hypothesis of no correlation surge is rejected in the stable range of roughly 10-20 percent before 2001-2, i.e., the evidence of structural change in the comovement can be found in less than 20% of all city-pairs. However, the rejection rate rose sharply to 60-80 percent around 2001-2. This jump in the rejection rate implies a drastic shift in the comovement of city-pair HPs, echoing our earlier findings on the comovement surge around the early 2000s.

3.3 Common factor model analysis

Another formal approach to examining the comovement surge is the common factor analysis. In the analysis of financial markets, factor representations are often used in the classical finance models like CAPM and APT to capture comovement of asset returns. And some researchers advocate the use of factor model based approach to gauging market comovement and market integration (e.g., Cotter et al. 2015, Pukthuanthong-Le and Roll 2009).[15] The basic idea of common factor model is to disentangle the portion of the movements of local HPs commonly shared across all cities (common component) from the one which is specific to that city (local component). In our case, this approach is equivalent to measuring the share of variability of local HP growths that can be attributable to common national factors (henceforth, common component share). If common national factors account for a larger portion of the local HP growth fluctuations as HPs comove together, local housing market can be viewed as more integrated to the rest of the nation. Although it is widely believed that the movements of local HP are mainly driven by local idiosyncratic factors, they are also subject to common national macroeconomic shocks by nature because the U.S. housing market is integrated with broader capital markets. Together with free capital mobility, these macroeconomic influences can potentially contribute to HP growth linkages across local housing markets.

Before moving on, it is instructive to probe the extent of the cross-sectional dependence (CSD) of HP changes to narrow down the sources behind the comovement jump. To this end, we employ the CD test proposed by Pesaran (2004), defined by $CD = TN(N-1)\hat{\bar{\rho}}/2 \xrightarrow{d} N(0,1)$. As displayed in Figure 6, the Pesaran's CD-test statistic is consistently larger than the critical value of 1.96 at the 5% significance level, indicative of the high correlation of HP growth among MSAs. More importantly, there is a big jump noticed in the CD-test statistic around the early 2000s, mimicking the drastic increase in the correlation measures above. Figure 6 also exhibits the CD-test statistics for defactored HP growth series ($\tilde{y}_{it}$) in which common factors, proxied by the cross-city average of HP growth $\frac{1}{N}\sum_{h=1}^{N} y_{ht}$, are removed from the local HP growth series.[16] As shown in Figure 6, however, we no

[15] Despite its popularity in measuring the integration of financial markets, correlation coefficients have been criticized for failing to capture the market integration properly when asset returns are driven by multiple common factors. In response, Pukthuanthong-Le and Roll (2009) and Cotter et al. (2015) advocate using factor based approaches that take a similar spirit with the common factor model considered here.

[16] The correlation of defactored series is conceptually related to the *excess comovement* adopted by Kallberg et al.

longer see a remarkable jump in the CD-test statistics for the defactored series as we did from the non-defactored series. This reinforces our view that the surge of comovement found in local HP growth is chiefly driven by a common national factor.

We then apply the following common factor model to our city-level HP growth data to evaluate the relative contribution of the common national factors to the movements of local housing prices,

$$\pi_{it} = a_i + \lambda_i' F_t + e_{it}, \tag{3}$$

where π_{it} denotes the HP growth rate in city i at time t, a_i represents a city fixed effect, F_t denotes common factors that capture common sources of variation in urban HP growths driven by aggregate shocks, λ_i is a factor loading that measures the *sensitivity* of HP change in city i to F_t, and e_{it} is an idiosyncratic error associated with city-specific events. City HP growths are correlated across cities by nature through the same common factors and the strength of these correlations hinge on the factor loadings, with the greater factor loading indicating the city HP moving more in sync with the common factor. The common component, or the product of common factor (F_t) and factor loadings (λ_i), is often the object of interest as it captures the HP growth in city i attributable to common national factors.

Table 3 reports the common component share of the city HP growth over different numbers of common factors. For the entire sample period, a single common factor can explain on average 41.7% (or median of 42.8%) of the total variability of the urban HP growths. It varies broadly across cities however. A single common factor can explain more than 75% of HP growth fluctuations in some cities, while its contribution is close to zero in the cities where HP growth volatility is fully explained by local component only. Table 3 also presents the subsample analysis results by dividing the sample around year 2000. Notice that the common component share has increased considerably after 2000, from less than 30 percent before 2000 to almost 65 percent in the post-2000 period, reinforcing our earlier findings on the surged HP comovements after 2000. This also accords with the findings by previous studies (e.g, Cotter et al. 2015, Del Negro and Otrok 2007, Fairchild et al. 2015) that national common factor became more important in explaining the movements of local HPs in more recent years.[17] Figure 7 visualizes this information by plotting the average common component share over different numbers of common factors. As Figure 7 demonstrates, the common component share has increased substantively after 2000 in all cases considered. It further shows that a single-factor representation is a reasonable choice because additional factors beyond the first one add relatively

(2014) as a measure of financial contagion. The excess comovement of HP change in city k at time t (r_{kt}) is estimated from the residual of $\hat{e}_{kt} = r_{kt} - \hat{\alpha}_{kt} - f_t \hat{\beta}_{kt}$ (eq.(3) in Kallberg et al. (2014)) where f_t and β_{kt} respectively represent common factor and factor loadings. Hence, it is defined as comovement among local HP changes beyond the degree that is justified by common fundamental factors.

[17] Del Negro and Otrok (2007) interpret the larger share of the common component found in the U.S. after the mid-90s as an increased integration in the regional mortgage markets.

little in explanatory power. Overall, our results in this section point to the importance of national common factor in explaining the increased comovement of city-level HPs. This certainly begs another question about which common factors can account for the large and sudden rise in the comovement. It is addressed in the following section.

3.4 Candidates of the common factor

Since the comovement jump is driven by factors at the national level, it is logical to conjecture that the driving force behind the comovement shift should be in a common set of nationwide economic shocks or policy changes related to the housing market, such as national income and inflation, monetary policy, and mortgage market innovations. Del Negro and Otrok (2007), however, claim that monetary policy shocks play only a limited role in explaining the housing price movements in the 2000s. Moreover, it is unlikely that national macroeconomic variables underwent such a sudden shift in the early 2000s.

Another potential candidate for the comovement surge is the onset of the financial crisis. Because the timing of the surge is very close to the outbreak of the financial crisis, one is tempted to view that the comovement surge might have been driven by the financial crisis which has increased the volatility of HP growth and consequently the comovement. Our vertict on this view is 'negative' on several grounds. First, as discussed earlier, a comovement jump still exists even after taking into account the volatility increase during the GFC in the mid-2000s. Second, our empirical analysis with various rolling windows indicates that the comovement surge occurred prior to the onset of the financial crisis, not at the outbreak of the financial crisis. Take the result from 6-year rolling window in Figure 4 for instance, the timing of the surge is around 2001, which corresponds to the sub-sample periods of 2001-2006. This implies that the comovement actually surged before the outbreak of the financial crisis in 2007. Third, we compare the evolutions of the HP growth correlations between two groups of city-pairs: in one group cities from the same states are paired (in-state group) and in the other group cities are paired with those from different states (out-of-state group). This exercise is conducted for 21 states where at least six cities are avaiable in each state. As shown in Figure 8, there exists a noticeable difference between the two groups in the dynamic pattern of correlation. In almost all the states considered, only a mild change is observed in the in-state group, while a sizable increase is noted in the correlation around the early 2000s in the out-of-stste group. To interpret, the comovement surge observed in the full sample must have come primarily from the city-pairs in different states. If the financial crisis is the main driver behind the comovement surge, then there is no compelling reason to expect the comovement surge to occur only in the out-of-state group. Our results therefore lend little support to the view that the recent financial crisis is responsible for the sudden and large surge in the comovement.

That being said, our finding that the comovement surge was noted mainly in the out-of-state city-pairs is intriguing and informative. This suggests that the driving force behind the comovement surge should be related to the common national factors that integrated housing markets across states, rather than within states. Then, a natural and logical choice for the driving force should be the one which brings down barriers to interstate housing market. Of relevance in this context is the role of financial integration in housing market integration through interstate banking and branching deregulations. In fact, the role of banking sector in transmitting housing market shocks to the entire economy has recently attracted enormous attention from researchers (e.g., Mian and Sufi, 2009, 2018). Studies in this direction tend to establish a close relationship between financial integration and housing market integration, typically using regulatory changes as an instrument to the evolution of local HP changes (e.g., Goetz and Gozzi 2019, Landier et al. 2017, Michalski and Ors 2012, Peek and Rosengren 2000). They commonly show that housing market integration took place across locations through a national banking channel. Peek and Rosengren (2000), for example, maintain that financial integration enhances the synchronization in housing markets and economic activity mainly through the propagation of credit supply shocks across the connected markets. A similar conclusion is reached by Landier et al. (2017) that the comovement rise in HPs can be explained to a great extent by geographic integration of banking markets after the interstate branching deregulations. Relatedly, Goetz and Gozzi (2019) find that banking integration increased the comovement of economic activity across U.S. states by fostering the transmission of regional shocks across states. Inspired by this, we focus on banking deregulations and the consequent financial integration among MSAs as the potential driver behind the surged comovement.[18]

4 Financial integration and movements of local HPs

4.1 Banking integration as the common factor

It is widely documented that financial markets in the U.S. became a lot more integrated after deregulations on the banking industry during the 1980s and 1990s.[19] With these regulatory changes in the banking industry, banks could operate across multiple states and localities, which subsequently led to a large wave of capital market integration in the U.S. (e.g., Goetz and Gozzi 2019, Morgan et

[18] We view that the national macroeconomic fundamentals like national employment and income are not much relevant for the increased comovements of local HPs on a couple of grounds. First, the comovement shift actually took place a bit earlier than the post-boom period when those fundamental variables are claimed to have played a pivotal role. Second, as shown in Table 2, the intercity dynamics of HP growths reveal a very different pattern from those of the fundamental macroeconomic variables. For instance, city-level income did not grow as fast as HP growth in particular after the mid-1990s.

[19] While statewide banking restictions were removed by the Depository Institutions and Deregulation and Monetary Control Act (DIDMCA) in 1980, interstate banking and interstate branching were not fully implemented until 1994 when the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) was passed. As presented in Table A.2, however, even with the IBBEA, states continue to exercise some authority to restrict or limit interstate entry (e.g., Loutskina and Strahan 2015). Illinois, for example, adopted interstate branching in 1997 but did not permit *de novo* branching by out-of-state banks until 2004 when it relaxed the relevant policies.

al. 2004, Loutskina and Strahan 2015). Since housing is a highly capital-intensive asset and financial intermediaries are an important source of mortgage lending, it is reasonable to posit that banks play an important role in the spatial comovement of regional HPs via their exposures to funding across states. This is consistent with the recent finding by Goetz and Gozzi (2019) that financial integration has a stronger positive effect on output comovement for industries with a high dependence on external finance like real estates. As reflected in the greater importance of common shock in explaining the variability of city HP growth, local HPs might have become more responsive to aggregate shocks through more integrated financial system after banking deregulations. This is reminiscent of the recent finding by Landier et al. (2017) that the incresed HP synchronization across U.S. states after banking deregulation was due largely to a greater integration of the U.S. banking industry. Related studies on credit supply channel of HPs (e.g., Mian and Sufi 2009, Adelino et al. 2012, Favara and Imbs 2015, to cite a few) also document that bank branching deregulation has triggered housing demand shocks through credit supply for banks, with the states experiencing larger HP increases where there was deregulation.[20]

Despite the intuition behind the potential role of banking deregulation in the comovement of HPs, its timing does not fit closely with that of the comovement surge. While the bank branching deregulation was officially implemented in 1994, the correlation jump did not take place until the early 2000s. As summarized in Table A.2 in the Appendix, however, this timing gap can be explained by the fact that bank branching deregulation was enacted by different states at different points in time and in many states it was not fully implemented until the 2000s (e.g., Rice and Strahan 2010). Landier et al. (2017) also claim that branching deregulation ended in 1994 with the Riegle-Neal Act, but the movement toward banking integration continued throughout the early 2000s when the HP comovement has surged.

Another plausible channel through which banking integration affected local HPs is the proliferation of mortgage securitization during the 2001-2006 housing boom, which is known to have enhanced the lending ability of banks in local housing markets (e.g., Loutskina and Strahan 2015). With the rapid growth of securitization, banking integration could exert a stronger influence on the comovement of HPs through large banks, especially after the repeal of the Glass-Steagall Act in 1999 (e.g., Fligstein and Goldstein 2011). For example, by acquiring J.P. Morgan in September 2000, Chase Manhattan could engage in underwriting or dealing in mortgage-backed securities (MBS) through the existing nationwide branches of the merged banks.[21] Securitization is also known to have contributed to a

[20] According to Landier et al.(2017), as much as one fourth of the increase in HP correlation over the 1976-1995 period can be attributable to the rise in banking integration, which mostly occurred through the expansion of the 20 largest bank holding companies across state boundaries.

[21] Banks were permitted to buy or sell securities based on assets such as mortgages even under the Glass-Steagall Act, but they were not allowed to underwrite or deal in MBS. From 2004 to 2006, about 80 percent of all mortgages were securitized (Keys et al. 2013) and most of the loans in the U.S. mortgage market are securitized by government-sponsored

rise in HPs across the nation by providing more credit to housing market, in particular to subprime borrowers (e.g., Mian and Sufi 2009). Investigating the relationship between securitization activity and the extension of subprime mortgage credit, Nadauld and Sherlund (2013) contend that securitization had an important impact on mortgage originations through its effect on lenders screening incentives.

4.2 Proxy measures of city-pair level financial integration

To assess the empirical relevance of the financial integration in explaining the comovement shift, we construct two novel proxy measures of city-pair level financial integration based on banks deposit data: (1) the share of out-of-state bank deposits; (2) the co-Herfindahl index of bank deposits. To this end, we exploit the information on total deposits, location, and ownership of all bank branches obtained from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD), available online ($https://www5.fdic.gov/sod/$) annually from 1994 onward.

Our first measure of the financial integration (FI) is the share of out-of-state bank deposits constructed as,

$$FI_{ij,t} = \theta_{i,t} \times \theta_{j,t}, \tag{4}$$

where $\theta_{i,t} = \frac{\sum_{h \notin} D^o_{i,h,t}}{\sum_{k=1}^{m} D_{i,k,t}}$ captures the fraction of deposits in city i at time t taken by banks running businesses outside their home states.[22] $D_{i,k,t}$ represents the deposits of bank k in city i in year t and $D^o_{i,h,t}$ denotes the deposit in city i in year t taken by bank h whose headquarters are located in other states. Then, $FI_{ij,t}$ effectively measures the degree to which city-pair i and j are financially integrated through banks operating nationally, or the extent to which each city is financially linked to the rest of the nation through nationwide banking system.[23] Although imperfect, this simple measure of financial integration is intuitive. National banks operating in multiple locations can transmit economic shocks via customers across different geographic areas by engaging in both lending to out-of-city borrowers and taking funds from out-of-city depositors. Because local banks typically borrow on the national wholesale market through national headquarters, the share of out-of-state bank deposits can gauge the extent of financial integration with the rest of the nation. In this vein, city-pairs with a larger share of the out-of-state bank deposits ($FI_{ij,t}$) can be viewed as financially more integrated because they are more connected to the rest of the nation through nationally operating banks.[24] Therefore,

enterprises (GSE) (e.g., Hurst et al. 2016).

[22] To illustrate this, take Abilene, TX, for example, there were 19 depository institutions taking deposits in 2017, of which only two banks, Bank of America and JPMorgan Chase Bank, are headquartered outside Texas. In 2017, the deposits taken by those two out-of-state banks account for 15.83% of the total deposits in the city, i.e., the city has the 15.83% of exposure to the rest of the nation through bank deposits. Hence, the share of out-of-state bank deposits in this city ($\theta_{i,t}$) is 0.1583. At the same time, the share of another city in Texas, Amarillo ($\theta_{j,t}$), is 0.177. Then, the degree of financial integration between the two Texan cities is 0.028 ($= 0.1583 \times 0.177$).

[23] Based on a similar data set, Loutskina and Strahan (2015) constructed a *state-level* measure of financial integration, 'deposit-based integration', by the fraction of deposits in a year owned by bank holding companies with deposits in other markets.

[24] To remind, banks were not allowed to open branches outside its home states until the interstate banking and interstate

cities with a larger share of out-of-state bank deposits are likely to have a stronger comovement of HPs through more integrated financial markets. Figure 9 plots the average share of out-of-state bank deposits since 1994. Over the years, an increasing share of deposits is created by out-of-state banks, consistent with the finding by Loutskina and Strahan (2015).

Another novel measure of financial integration constructed here is the co-Herfindahl index for city-pair i and j at time t ($H_{ij,t}$), which is given by

$$H_{ij,t} = \sum_{k=1}^{m} s_{i,t}^{k} \times s_{j,t}^{k}, \tag{5}$$

where $s_{h,t}^{k}$ denotes the market share of bank k in city h, in terms of outstanding deposits at t. This index therefore captures the sum of deposit market share of banks ($k = 1, ..., m$) operating in both cities i and j at time t. Note that this index is constructed in each city-pair every year. The basic idea of this measure is that if the deposit share of a bank is high in one city (i) but low in another (j), then the co-Herfindahl index will be low because the two cities are not much connected each other through common banks running business in both cities. Intuitively, city-pairs with higher market concentrations of the common banks are likely to experience stronger comovement of HPs. Figure 10 displays the evolution of average co-Herfindahl index over time for both in-state city-pairs (solid line) and out-of-state city-pairs (dotted line). It should be noted that the index for the out-of-state city-pairs has risen steadily over time, while that of the in-state city-pairs remained quite stable. This result corroborates our insight on the role of interstate banking deregulations and the ensued financial integration.

Having said that, there exist a couple of legitimate concerns regarding the use of our deposit-based measures of financial integration for further analysis. First, loans are generally more directly related to local HPs than deposits and deposits collected in a city is not necessarily equal to the loans made in the same city. This is particularly the case in light of the fact that loan markets are prone to be national in scope, while deposit markets are likely to be more local in scope (e.g., Egan et al., 2017). However, since the correlations between deposit and loan are high in many metropolitan areas as often documented in the literature, deposits can be considered as an unbiased measure of lending activity (e.g., Cuñat et al., 2018).[25] Second and more important, it is empirically challenging to establish the causality from financial integration to the comovement of HPs. One may suspect that our deposit-based measures of financial integration could be endogenous to HP changes if banks choose to expand their business into the regions where HPs grew faster before banking deregulations. If banks open more branches

branching were fully adopted in 1994 and even after 1994 there is a large variation across states in the full implementation of the bank branching deregulation. Since the DIDMCA of 1980 allowed banks to operate statewide business only, it is conceivable that the degree of financial integration was virtually zero until 1994.

[25] Landier et al. (2017) find that the correlation between deposit co-Herfindhals and lending co-Herfindhals is as high as 0.76. They also show that the regression results based on both measures are qualitatively very similar.

in the areas where HP grew faster before the deregulations, then the degree of financial integration will be highly correlated with the past HP growth. With the well-known persistence of HP growth series (e.g., Glaeser and Nathanson 2017, Guren 2018), this correlation naturally induces a positive association between financial integration measure and (future) HPs growths, or the endogeneity of financial integration to HP growths. To bear this out, we plot in the top panel of Figure 11 the average city HP growth rates before 1995 (on the vertical axis) against the average level of financial integration in the post-1995 period (on the horizontal axis). If financial integration is indeed endogenous with respect to HP growths in such a way that banks extended their businesses in the areas that had experienced a faster growth in HPs previously, then the two variables should be positively correlated. As can be seen from the top panel of Figure 11, however, there is little indication of any meaningful relationship between the two, lending little credence to the endogeneity argument.[26]

4.3 Explanatory power of financial integration on local HP movements

As a preliminary assessment of the impact of city-level financial integration on local HP movements, we look into their explanatory power on the movements of local HPs. The following cross-sectional regression is performed to evaluate how well financial integration can explain the cross-city differences in local HP growth rates, while controlling for other key explanatory variables.[27]

$$\Delta\widehat{HP}_{iT} = \alpha + \beta_1 FI_{iT} + \beta_2 SC_i + \beta_3 FI_{iT} \times SC_i + Z'_{iT}\gamma + \varepsilon_i, \quad i = 1, ..., N, \tag{6}$$

where $\Delta\widehat{HP}_{iT}(= \frac{1}{T}\sum_{t=1}^{T}\Delta HP_{it})$ is the average growth rate of HP in city i for the sample period $t = 1, ..., T$. FI_{iT} denotes the degree of financial integration in city i, measured by the share of out-of-state banks in city i in eq.(4) or the average co-Herfindahl index in eq.(5). We present results using both measures of financial integration. SC_i is the housing supply constraints in city i measured by the Saiz's supply elasticity (SAIZ) or the Wharton Residential Land Use Regulation Index (WRLURI). The product term of financial integration and housing market constraint ($FI_i \times SC_i$) is to capture the interplay between city-level financial integration and city-level regulation on housing supply.[28] Z denotes a set of other city-level control variables including per capita income growth, population growth, and per capita deposit growth: $Z \in \{\Delta\widehat{Inc}_{it}, \Delta\widehat{Pop}_{it}, \Delta\widehat{Dep}_{it}\}$, where Inc_{it}, Pop_{it}, and Dep_{it} respectively denote per capita income, population, and per capita bank deposit in city i at time t. To account for the possible breaks in the dynamics of HP growths, the regression is run on three separate subperiods, up to 1994:Q4, 1995:Q1-2006.Q4, and after 2007:Q1, bearing the timing of bank branching

[26] Similarly, Goetz and Gozzi (2019) find no relationship between the timing of interstate banking deregulation between states and their prior levels of and changes in bilateral output comovement.

[27] Refer to Appendix B for the discussion of the explanatory variables used in our regression analysis throughout the paper.

[28] As highlighted by Davidoff (2015), this product term is also useful for addressing the enodogeneity issue arising from the use of housing supply constraint as an instrument for housing market fundamentals.

deregulation (year 1994) and housing market crash (year 2007) in our mind.

The top panel of Table 4 reports the regression results from the subperiod of 1975-1994 for two model specifications with different measures of housing market constraint, WRLURI for model 1 and SAIZ for model 2. We first note that the estimated coefficients on the financial integration measures (FI_i) are statistically insignificant in both model specifications, implying that financial integration does not have much explanatory power for the HP growth rates as before 1995. The results are robust to alternative measures of financial integration. Since financial integration in this regression exercise is measured for the subperiod 1994-2000, this outcome suggests no significant association between the pre-1995 HP growth rates and financial integration after 1995, or the lack of endogenous interaction between financial integration and HP growths. This corroborates our graphic evidence shown in the top panel of Figure 11 that financial integration must have proceeded across U.S. cities irrespective of prior local housing market conditions.

The story changes somewhat significantly when we look at the middle panel of Table 4, for the subperiod of 1995-2006. Here the HP growth rates of the subperiod of 1975-1994 are augmented to capture the well-known persistence of HP movements over time. Now, the coefficient of financial integration (β_1) is positive and significant, consistent with the idea that HP has grown faster in the cities which are financially more connected to the rest of the nation. Put differently, on average cities experience a faster growth of HP if they are more financially integrated to other cities. When the co-Herfindahl index is used for the financial integration measure, the quantitative effect of financial integration on the HP growth is 0.5574, meaning that a 1% rise in the co-Herfindahl index raises local HPs by more than a half percentage point, after controlling for other explanatory variables. Moreover, the interaction term of financial integration with housing supply constraints ($FI_{iT} \times SC_i$) also turns out to be significant with the anticipated positive signs. To interpret, the impact of financial integration on HP growth is stronger in the cities with heavier regulation on housing supply. By contrast, unlike the large literature on the importance of housing supply constraints, we fail to find any compelling evidence on the significance of SAIZ or WRLURI on its own in explaining local HP growths. Cities with heavier regulations on housing market might have a higher level of HPs on average, but not necessarily a faster growth of HP.

A similar conclusion is reached in the bottom panel of Table 4 for the last subperiod. It is quite similar to the results in the middle panel of the table, except that financial integration now has a negative impact on the HP growth, due mainly to the housing market bust during the financial crisis. In addition, the magnitude of the financial integration effects is a lot smaller after 2007, and so is the impact of its interaction term with housing supply constraints.

5 Pairwise regression analysis

Since our proxy measures of financial integration are empirically relevant for explaining the city-level HP growths, we now investigate the role of financial integration in explaining the comovement shifts of local HPs, which is the object of our ultimate interest. For this purpose, we carry out a battery of pairwise regression analysis based on 28,441 ($= \frac{239 \times 238}{2}$) pairs of metropolitan areas. The first regression is run on city-pair comovement of HP growth *per se* and the second regression is performed on the *change* in the comovement of HPs after 2000. To ensure that our results are robust to the choice of comovement measure, we consider two different measures of comovements as dependent variable: (1) the heteroskedasticity-corrected correlation of HP growth between cities i and j ($\hat{\rho}_{ij}$); and (2) an R-square based correlation coefficient (henceforth, $\hat{b}_{ij}$) as in Cotter et al. (2015).[29]

5.1 The impact of financial integration on the comovement of HP growth

Prior to examining how and to what extent financial integration can explain the surge in the comovement of local HPs, we first consider the following city-pair regression model,

$$y_{ij} = \alpha_0 + \beta FI_{ij} + X'_{ij}\delta + Z'_{ij}\gamma + \epsilon_{ij}, \tag{7}$$

where y_{ij} denotes the bilateral comovement of HP growths between cities i and j for a given sample period. Both $Corr(\Delta HP_i, \Delta HP_j)$ and $\hat{b}_{ij}$ are used for y_{ij}. Standard errors are clustered at the state-pair level. Again, the variable of interest is the city-pair financial integration between cities i and j (FI_{ij}) proxied by the aforementioned two measures. The coefficient β estimates the impact of FI on bilateral comovement of HP growths. For other explanatory variables, we consider two sets of city-pair characteristics, X_{ij} and Z_{ij}. X contains conventional fundamental variables of HP determination, such that $X \in \{Corr(\Delta Inc_i, \Delta Inc_j), Corr(\Delta Pop_i, \Delta Pop_j), Corr(\Delta Dep_i, \Delta Dep_j)\}$, where Inc, Pop, and Dep respectively represent per capita income, population, and per capita bank deposits as before. Positive signs are expected for the coefficient δ because city-pairs with more similar movements of fundamentals are likely to experience a stronger comovement of HP growths. Z encompasses additional local control variables, $Z \in \{SC_{ij}, \log DIST_{ij}, STATEDUM_{ij}\}$. '$SC_{ij}$' denotes the difference in the housing supply constraint between two cities measured by $[max(x_i, x_j) - min(x_i, x_j)]/max(x_i, x_j)$ where x_h denotes the WRLURI variable for city h. A negative sign is expected for 'SC_{ij}' because city-pairs with dissimilar levels of housing market constraints are likely to have a weaker comovement of HP growths. Z also includes spatial variables like physical distance ($DIST$) and state dummy variables ($STATEDUM$), which are known to have significant impacts on the geographic differences in HP. $DIST_{ij}$ is expected to have a negative effect on the comovement of HP growths because distance

[29] The R-square based measure of comovement ($\hat{b}_{ij}$) is estimated from $\Delta HP_{it} = a_{ij} + b_{ij}\Delta HP_{jt} + e_{ij}$.

between two cities impedes interactions between regional housing markets, such that city-pairs that are geographically farther apart are liable to have weaker comovements of HP growths.[30] $STATEDUM_{ij}$ is an in-state dummy variable which takes on the value of one if cities i and j are in the same state and zero otherwise. This dummy variable is to capture all the in-state effects embracing the state level policy environments and state-tax. $STATEDUM$ is expected to enter with a positive sign because cities in the same state are likely to have stronger comovement of HP growths, because of more homogeneous economic environments and regulations. Standard errors are clustered at the city-pair level.

The results of this regression exercise is presented in Table 5, using both the correlation (on the left panel) and the R-square based comovement measure (on the right panel) as dependent variable. Robust standard errors are shown in parentheses. Both measures of comovements yield qualitatively similar results with regard to our main conclusions. They largely conform to our original intuition about the effects of the key explanatory variables on the comovement of HP growths: significant positive effects of financial integration (FI) and city-pair correlation of other fundamental variables, but significant negative effects of housing supply constraint difference (SC) and physical distance ($DIST$). Not surprisingly, the comovement of HP growths is stronger between cities that are more integrated financially and economically. This is consistent with the visual evidence shown in the bottom panel of Figure 11, where the degree of financial integration is moderately positively associated with the comovement of HP growths. The coefficient for '$STATEDUM'$ is statistically significant and takes an anticipated positive sign, suggesting that in-state city-pairs are likely to have a stronger comovement of HP growths thanks to similar statewide economic and policy environments. Along similar lines, physical distance ($DIST$) has a significant negative coefficient, indicating that city-pairs tend to have a weaker comovement of HP growths when they are spatially farther apart. The significance of both state dummy variable and physical distance suggests that state boundaries may contain more information than simple geographic proximity in explaining the comovement of HP growths. Interestingly, the impact of housing market constraints (SC) is now negative and statistically significant in most cases under study. Using the R-square based measure of comovement ($\hat{b}_{ij}$) as dependent variable leaves the regression results virtually unaltered.

The finding of a positive effect of financial integration on the comovement of local HP growths between cities (Our finding that HPs growths comove more strongly between cities that are financially more integrated) is interesting and provides some useful insights on the theoretical contributions. It suggests that financial integration contributed to the more homogeneous movements of city HPs possibly through the transmission of economic shocks on housing markets across locations. As highlighted

[30] The physical distance between cities i and j is measured by the greater-circle distance or orthodromic distance as the shortest distance between two cities.

by Goetz and Gozzi (2019), however, the effect of financial integration (through banks) on the comovement of economic activity between regions is theoretically ambiguous and hinges on the nature of the shocks. Theoretically, financial integration may reduce the comovement of economic activity between regions in the presence of idiosyncratic real (e.g., productivity) shocks as multi-market banks move funds from busting areas facing a negative productivity shock to non-affected regions.[31] In this case, with financial integration funds flow from areas with weaker housing markets, where HP drops, toward areas with stronger housing markets, where HP rises, leading to a divergence in HPs between regions and hence reducing the comovement. On the other hand, financial integration can increase the comovement between regions if multi-market banks respond to shocks originating in one region by changing their operation in other regions where they are active through internal capital markets (e.g., Goetz and Gozzi 2019). For instance, nationally operating banks facing a negative funding shock in one market may cut lending in other markets (e.g., Morgan et al. 2004). In this case, a negative shock in one region transmits to another region through banks and thus increases the comovement of HP growths. Given the theoretical ambiguity, the impact of financial integration on the comovement of HPs seems to be essentially an empirical question, but the empirical literature on this issue is also divided into two fronts. A recent empirical contribution by Loutskina and Strahan (2015) shows that financial integration in the U.S. through nationwide branching deregulations led to divergence in economic growth across areas by amplifying the effects of housing shocks on real economic activity. By contrast, analyzing the effect of the geographic expansion of banks across U.S. states on the comovement of economic activity between states, Goetz and Gozzi (2019) find that bilateral banking integration increases output comovement between states. The authors further show that banking integration has a strong positive effect on output synchronization for industries with a high dependence on external finance such as housing markets, while it does not for industries that are less dependent on external financing. Our empirical findings support the second camp by showing that financial integration has contributed to the increased comovement of city-pair HP growths.

5.2 The impact of financial integration on the comovement shift

Now we turn to the impact of financial integration on the comovement surge around 2000. The following pairwise regression model bears this out.

$$\Delta y_{ij} = \alpha + \beta FI_{ij} + \Delta X_{ij}'\delta + Z_{ij}'\gamma + \varepsilon_{ij}. \tag{8}$$

Beware that the dependent variable (Δy_{ij}) is now the *change* in the comovement after 2000 where y_{ij} denotes $Corr(\Delta HP_i, \Delta HP_j)$ or $\hat{b}_{ij}$ as before. The set of explanatory variables remains the same except that ΔX_{ij} is now used instead of X_{ij}, where ΔX_{ij} includes the *changes* in the city-pair correlation

[31] Similarly, in the business cycle literature, it is broadly documented that financial integration hampers business cycle synchronization as output growth among financially integrated areas is negatively correlated.

of per capita income growth, population growth, and per capita deposit growth after 2000. Again, financial integration (FI_{ij}) is expected to have a positive sign because financially more integrated city-pairs are likely to have a bigger increase in the comovement after 2000. We also anticipate a positive sign for the coefficients of ΔX_{ij} because city-pairs with a greater increase in the comovement of fundamental variables are likely to have a greater increase in the comovement of HP growths. The other explanatory variables, $DIST_{ij}$ and SC_{ij}, are expected to have a negative sign as before, i.e., the comovement increase after 2000 is smaller for the city-pairs that are located farther apart or that have more disparate levels of housing supply constraints. As before, standard errors are clustered at the state-pair level.

Table 6 presents the results from this regression exercise. The results in the table seem to be qualitatively similar to those reported in Table 5, but with some notable exceptions. Surprisingly, financial integration now takes an unexpected negative sign, i.e., city-pairs with a stronger financial integration have experienced a smaller increase in the HP comovement after 2000. On the flipside, this implies a larger comovement increase in the city-pairs that were financially less connected before. This outcome is somewhat puzzling at first in light of our earlier findings on the positive effect of financial integration on the HP movements. On closer examination, however, a potentially logical explanation comes to the fore. A plausible explanation for this seemingly puzzling outcome is that financial integration after banking deregulations might have mainly influenced housing markets that were financially less connected prior to the banking deregulations. Put alternatively, the benefit of financial integration primarily came from linking financially segmented cities through nationwide banking. Housing markets that were formerly segmented got newly connected to other markets in the country through newly opened branches of the nationally operating banks. That must have led to a surge in the comovement of local HPs after 2000. A similar story is told from the variables of 'DIST' and 'STATEDUM', whose signs are now flipped as well, i.e., city-pairs that are either geographically farther apart, or those from different states, are found to have experienced a greater increase in the comovement after 2000. This is in line with our earlier observation that the correlation of HP growths among cities in the same states was already high even before the banking deregulations and did not change much afterwards. The impacts of other explanatory variables are similar to those reported in Table 5, which largely conform to our economic intuition. City-pairs that had a greater increase in the comovement of fundamental variables had a larger increase in the HP comovement after 2000. By contrast, city-pairs with different levels of housing supply constraints had a smaller increase in the comovement after 2000. Overall, our regression results disclose that financial integration played a significant role in the comovement surge of local HPs after 2000, primarily by linking cities that were financially less connected previously.

5.3 Robustness checks

Since our empitical results are obtained from a specific sample, the main conclusions drawn so far could be sensitive to the choice of samples. In this section we consider several robustness checks on our results across variations in samples.[32] First, one legitimate concern might be that our results are based on a specific breakpoint, specifically year 2000. In response, we consider 1995 as an alternative breakpoint in the sense that it is the first year after the bank branching deregulation was implemented and hence is closely tied to the financial integration argument maintained in this study. Moreover, 1995 is approximately half way through the sample period under study. We find that our results are largely invariant to this alternative breakpoint. Second, it is also possible that our results might have been heavily influenced by institutional and structural changes in the U.S. housing market in the early 1980s. This leads us to redo the analysis by changing the sample starting point as 1985, effectively removing the influence of the noisy and volatile movements of HPs in the late 1970s and the early 1980s. The results reported in the online Appendix show that our conclusions are robust to this variation as well. Third, one may worry that the unconventional monetary policy in the post-2008 period could affect the result. To address this concern, we re-estimate our regression using the pre-2008 sample only after dropping the observations of the post-2008 period. Our results from this alternative sample period are also very similar to those from the full sample analysis. Fourth, we control for the local macroeconomic environments by augmenting the correlation of fundamentals across cities, namely the correlation of changes in city-level unemployment rates (which is available only after 1990, however). Our results are unaltered by this change. Fifth, we investigate whether our empirical results are unduly driven by some outlier MSAs of our data. It is well established in the literature that a small number of outliers called "superstar cities", which are known to have experienced considerably higher price growth but low population growth (e.g., Gyourko et al. 2008), are responsible for skewing the distribution of city-level HPs. In response, we drop the top ten percent of the fastest growing cities from our dataset and find that our main conclusions still hold up. We also examine whether our results are sturdy when the sample is divided into two subgroups based on city size, large- (with the average population of more than 500,000) versus small-size (with the average population upto 500,000) cities. Similar results are obtained when the regression is run on the two separate subgroups. Finally, we re-ran our regression analysis using the CoreLogic dataset that covers homes purchased with non-conforming mortgages as well. We find results similar to those reported throughout the paper.

To sum, we could verify that our central findings in the current study are quite robust to a number of variations in samples.

[32] These results are not reported here to preserve space, but will be available in the online Appendix posted at the author's website.

6 Concluding remarks

The past decade has seen the emergence of a substantive and influential body of research on the housing markets, especially after the subprime mortgage crisis in the mid-2000s when the U.S. housing market has undergone dramatic changes. Whereas the literature in this direction is quite voluminous, our understanding of local HP movements is rather limited at the MSA level because the previous studies in this direction have largely focused on a small subset of cities or for a relatively short sample span. We attempt to fill this void by analyzing the dynamics of quarterly single-family home price data for 239 U.S. MSAs over the past four decades. In line with what is often documented in the previous literature, we find substantial variations in local HPs across metropolitan areas and the rising geographic disparities over time. At the same time, however, local HPs have grown a lot more synchronously after 2000 when the average cross-city correlation of HP growths has risen sharply from 0.2 to 0.7. Decomposing HP movements into components attributable to common national factor embodied in all local housing markets and idiosyncratic factors that affect only local markets, we find that the share of the common national factors has increased significantly after 2000, from less than 30% to almost to two-thirds. This comovement surge, however, is hard to reconcile with the conventional wisdom that local HPs are, to a great extent, locally determined and geographically segmented from other local housing markets.

Of the various potential candidates considered, we find that regional financial integration after banking deregulations played an important role for the comovement surge, partly because it is well aligned with similar developments in the financial sectors across cities after the deregulations in banking industry, and because the timing of the comovement shift coincides with the advent of full-fledged effects of banking deregulations in the early 2000s. Financial integration facilitates capital mobility and hence fosters the propagation of local shocks across the nation. Using two proxy measures of the city-level financial integration constructed here, we find that financial integration has a significant explanatory power on the comovement of local HPs. On average, city-pairs with stronger financial integration, typically through nationally operating banks, tend to have a greater comovement of local HPs. Financial integration, however, has led to a greater comovement shift after 2000 in the city-pairs that were previously more segmented financially and economically. After deregulations in the U.S. banking industry, housing markets that were less connected in the past have become more integrated through the geographic expansion of banks across U.S. states. Financial integration due to banking deregulations must have contributed to the stronger linkages of local housing markets primarily through the cities that were previously segmented from the rest of the nation financially and geographically. We have checked the robustness of our results along several dimensions. Our key conclusions withstand a set of robustness checks as none of these extensions has a significant impact on our findings.

Our study on the comovement surge of local HP growths offers novel insights into the change in the dynamics of local HPs after regulatory changes in the banking industry. Stronger comovement of local HPs due to increased financial integration following banking deregulation implies that local housing market shocks can transmit to other housing markets through nationally operating banks. Given the close linkage between housing and financial markets, this certainly poses a greater challenge to policy makers at the both regional and national levels.

References

[1] Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2012. "Credit Supply and HPs: Evidence from Mortgage Market Segmentation." NBER Working Paper No. 17832, National Bureau of Economic Research.

[2] Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005. "Comovement." *Journal of Financial Economics*, 75, 283–317.

[3] Case, Karl E. and Robert J. Shiller, 1996. "Mortgage Default Risk and Real Estate Prices: The Use of Index-Based Futures and Options in Real Estate." *Journal of Housing Research*, 7(2), 243–258.

[4] Chiang, Thomas C., Bang Nam Jeon, and Huimin Li, 2007. "Dynamic Correlation Analysis of Financial Contagion: Evidence from Asian Markets." *Journal of International Money and Finance*, 26, 1206–1228.

[5] Cotter, John, Stuart Gabriel, and Richard Roll, 2015. "Can Housing Risk Be Diversified? A Cautionary Tale from the Housing Boom and Bust." *Review of Financial Studies*, 28(3), 913–936.

[6] Cuñat, Vicente, Dragana Cvijanović, and Kathy Yuan, 2018. "Within-Bank Spillovers of Real Estate Shocks." *Review of Corporate Finance Studies*, 7(2), 157–193.

[7] Davidoff, Thomas, 2013. "Supply Elasticity and the Housing Cycle of the 2000s." *Real Estate Economics*, 41(4), 793–813.

[8] Davidoff, Thomas, 2015. "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors." Working Paper, University of British Columbia.

[9] DeFusco, Anthony, Wenjie Ding, Fernando Ferreira, and Joseph Gyourko, 2018. "The Role of Price Spillovers in the American Housing Boom." *Journal of Urban Economics*, 108, 72–84.

[10] Del Negro, Marco and Christopher Otrok, 2007. "99 Luftballons: Monetary Policy and the HP Boom across U.S. States." *Journal of Monetary Economics*, 54, 1962–1985.

[11] Egan, Mark, Ali Hortacsu, and Gregor Matvos, 2017. "Deposit Competition and Financial Fragility: Evidence from the US Banking Sector." *American Economic Review*, 107, 169–216.

[12] Fairchild, Joseph, Jun Ma, and Shu Wu, 2015. "Understanding Housing Market Volatility." *Journal of Money, Credit and Banking*, 47(7), 1309–1337.

[13] Favara, Giovanni, and Jean Imbs, 2015. "Credit Supply and the Price of Housing." *American Economic Review*, 105(3), 958–92.

[14] Ferreira, Fernando, and Joseph Gyourko, 2014. "Anatomy of the Beginning of the Housing Boom: U.S. Neighborhoods and Metropolitan Areas, 1993-2009." NBER Working Paper No. 17374, National Bureau of Economic Research.

[15] Fligstein, Neil, and Adam Goldstein, 2011. "Catalyst of Disaster: Subprime Mortgage Securitization and the Roots of the Great Recession." IRLE Working Paper No.113-12, University of California, Berkeley.

[16] Forbes, Kristin J., and Roberto Rigobon, 2002, "No Contagion, Only Interdependence: Measuring Stock Market Comovements." *Journal of Finance*, LVII(5), 2223–2261.

[17] Glaeser, Edward L., and Charles G. Nathanson, 2017. "An Extrapolative Model of HP Dynamics." *Journal of Financial Economics*, 126, 147–170.

[18] Goetz, Martin R., 2018. "Competition and Bank Stability." *Journal of Financial Intermediation*, 35, 57–69.

[19] Goetz, Martin R. and Juan C. Gozzi, 2019, "Financial Integration and the Co-Movement of Economic Activity: Evidence from U.S. States." *mimeo*. Available at SSRN: https://ssrn.com/abstract=2362274 or http://dx.doi.org/10.2139/ssrn.2362274

[20] Guren, Adam M., 2018. "HP Momentum and Strategic Complementarity." *Journal of Political Economy*, 126(3), 1172–1218.

[21] Gyourko, Joseph, Albert Saiz, and Anita Summers, 2008. "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index." *Urban Studies*, 45(3), 693–729.

[22] Gyourko, Joseph, Christopher Mayer, and Todd Sinai, 2013. "Superstar Cities." *American Economic Journal: Economic Policy*, 5, 167–199.

[23] Hurst, Erik, Benjamin J. Keys, Amit Seru, and Joseph Vavra, 2016. "Regional Redistribution through the US Mortgage Market." *American Economic Review*, 106(10), 2982–3028.

[24] Kallberg, Jarl G., Crocker H. Liu, and Paolo Pasquariello, 2014. "On the Price Comovement of U.S. Residential Real Estate Markets." *Real Estate Economics*, 42(1), 71–108.

[25] Keys, Benjamin J., Tomasz Piskorski, Amit Seru, and Vikrant Vig, 2013. "Mortgage Financing in the Housing Boom and Bust." In *Housing and the Financial Crisis*, edited by Edward L. Glaeser and Todd Sinai, 143–205. Chicago: University of Chicago Press.

[26] Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman, 2003. "International Business Cycles: World, Region and Country Specific Factors." *American Economic Review*, 93, 1216–1239.

[27] Landier, Augustin, David Sraer, and David Thesmar, 2017. "Banking Integration and HP Comovement." *Journal of Financial Economics*, 125, 1–25.

[28] Loutskina, Elena, Philip E. Strahan, 2015. "Financial Integration, Housing, and Economic Volatility." *Journal of Financial Economics*, 115, 25–41.

[29] Luciani, Matteo, 2015. "Monetary Policy and the Housing Market: A Structural Factor Analysis." *Journal of Applied Econometrics*, 30, 199–218.

[30] Mian, Atif, and Amir Sufi, 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *Quarterly Journal of Economics*, 124(4), 1449–1496.

[31] Mian, Atif, and Amir Sufi, 2018. "Credit Supply and Housing Speculation." NBER Working Papers No. 24823, National Bureau of Economic Research.

[32] Miao, Hong, Sanjay Ramchander, and Marc W. Simpson, 2011. "Return and Volatility Transmission in US Housing Markets." *Real Estate Economics*, 39(4), 701–741.

[33] Michalski, Tomasz, and Evren Ors, 2012. "(Interstate) Banking and (Interstate) Trade: Does Real Integration Follow Financial Integration?" *Journal of Financial Economics*, 104(1), 89–117.

[34] Morgan, Donald P., Bertrand Rime, and Philip E. Strahan, 2004. "Bank Integration and State Business Cycles." *Quarterly Journal of Economics*, 119(4), 1555-84.

[35] Morrison, D., 1983. Applied Linear Statistical Methods. Prentice-Hall, Inc., New Jersey.

[36] Nadauld, Taylor D.,and Shane M. Sherlund, 2013. "The Impact of Securitization on the Expansion of Subprime Credit." *Journal of Financial Economics*, 107, 454–476.

[37] Nagaraja, Chaitra H., Lawrence D. Browny, and Susan M. Wachter, 2010. "House Price Index Methodology." mimeo, The Wharton School, University of Pennsylvania.

[38] Paciorek, Andrew, 2013. "Supply Constraints and Housing Market Dynamics." *Journal of Urban Economics*, 77, 11–26.

[39] Pasquariello, Paolo, 2007. "Imperfect Competition, Information Heterogeneity, and Financial Contagion." *Review of Financial Studies*, 20, 391–426.

[40] Peek, Joe, and Eric S. Rosengren, 2000. "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States." *American Economic Review*, 90(1), 30–45.

[41] Pesaran, M. Hashem, 2004. "General Diagnostic Tests for Cross Section Dependence in Panels." CESifo Working Paper 1229, IZA Discussion Paper 1240.

[42] Pukthuanthong-Le, K., and R. Roll. 2009. "Global Market Integration: An Alternative Measure and Its Application." *Journal of Financial Economics*, 94, 214–32.

[43] Rice, Tara and Philip E. Strahan, 2010. "Does Credit Competition Affect Small-Firm Finance?" *Journal of Finance*, 65(3), 861–889.

[44] Saiz, Albert, 2010. "The Geographic Determinants of Housing Supply." *Quarterly Economic Journal*, 125(3), 1253–1296.

[45] Van Nieuwerburgh, Stijn, and Pierre-Olivier Weill, 2010. "Why Has HP Dispersion Gone Up?" *Review of Economic Studies*, 77, 1567–1606.

[46] Zhu, Bing, Roland Füss, and Nico B. Rottke, 2013. "Spatial linkages in returns and volatilities among US regional housing markets." *Real Estate Economics*, 41(1), 29–64.

Appendix A: Data Description

Table A.1: Description of city-level characteristics

Variable	Description	Source
HP	Quarterly HP index from the Federal Housing Finance Agency (FHFA) combined with home price data from the ACCRA during 1975.Q1-2017.Q3	OFHEO ACCRA
Distance	The great circle distance computed by using the latitude and longitude of each city	The American Practical Navigator (relevant website)
Income	Per capita personal income of the U.S. Metropolitan area during 1976-2016	BEA website
Population	Average populations of the U.S. Metropolitan area during 1976-2016	Census Bureau website
Bank deposit	Annual total deposits by the all branches of all insured banks during 1994-2017	Summary of Deposits at the FDIC website
Housing market constraints	The Saiz's house supply elasticities and WRLURI index	WRLURI and Saiz websites

Table A.2: Number of cities by states

State	Number of cities	Effective date	State	Number of cities	Effective date	State	Number of cities	Effective date
AL	6	5/31/1997	MA	3	8/2/1996	OH	11	5/21/1997
AR	3	6/1/1997	MD	2	9/29/1995	OK	3	5/17/2000
AZ	5	8/31/2001	ME	2	1/1/1997	OR	6	7/1/1997
CA	15	9/28/1995	MI	10	11/29/1995	PA	10	7/6/1995
CO	6	6/1/1997	MN	2	6/1/1997	RI	1	6/20/1995
CT	3	6/27/1995	MO	7	9/29/1995	SC	7	7/1/1996
DE	1	9/29/1995	MS	2	6/1/1997	SD	1	3/9/1996
FL	9	6/1/1997	MT	1	10/1/2001	TN	6	3/17/2003
GA	7	5/10/2002	NC	12	7/1/1995	TX	18	9/1/1999
IA	7	4/4/1996	ND	2	8/1/2003	UT	3	4/30/2001
ID	2	9/29/1995	NE	2	5/31/1997	VA	4	9/29/1995
IL	6	8/20/2004	NH	1	1/1/2002	VT	1	1/1/2001
IN	7	7/1/1998	NJ	1	4/17/1996	WA	6	5/9/2005
KS	3	9/29/1995	NM	3	6/1/1996	WI	9	5/1/1996
KY	3	3/22/2004	NV	3	9/29/1995	WV	2	5/31/1997
LA	6	6/1/1997	NY	8	6/1/1997	WY	1	5/31/1997

Note: 'Effective date' denotes the effective date of interstate branching regulation changes which we borrowed from Rice and Strahan (2010). For the states which have multiple effective dates, we choose the last one. See also Goetz (2018) on the effective dates of changes to state laws that affect the ability of banks to expand across state borders.

Table A.3: 239 MSAs in the continental U.S.

Abilene, TX	Flint, MI	New Orleans-Metairie-Kenner, LA
Akron, OH	Florence, SC	New York-Northern New Jersey-Long Island, NY-NJ-PA
Albany, GA	Fond du Lac, WI	Niles-Benton Harbor, MI
Albany-Schenectady-Troy, NY	Fort Collins-Loveland, CO	Norwich-New London, CT
Albuquerque, NM	Fort Smith, AR-OK	Oklahoma City, OK
Alexandria, LA	Fort Wayne, IN	Olympia, WA
Allentown-Bethlehem-Easton, PA-NJ	Fresno, CA	Omaha-Council Bluffs, NE-IA
Amarillo, TX	Gainesville, FL	Orlando-Kissimmee, FL
Ames, IA	Grand Junction, CO	Oshkosh-Neenah, WI
Ann Arbor, MI	Grand Rapids-Wyoming, MI	Oxnard-Thousand Oaks-Ventura, CA
Appleton, WI	Greeley, CO /1	Palm Bay-Melbourne-Titusville, FL
Asheville, NC	Green Bay, WI	Pensacola-Ferry Pass-Brent, FL
Atlanta-Sandy Springs-Marietta, GA	Greensboro-High Point, NC	Peoria, IL
Austin-Round Rock, TX	Greenville, NC	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
Bakersfield, CA	Greenville-Mauldin-Easley, SC	Phoenix-Mesa-Scottsdale, AZ
Baltimore-Towson, MD	Gulfport-Biloxi, MS	Pittsburgh, PA
Baton Rouge, LA	Hagerstown-Martinsburg, MD-WV	Pocatello, ID
Beaumont-Port Arthur, TX	Harrisburg-Carlisle, PA	Portland-South Portland-Biddeford, ME
Bend, OR	Hartford-West Hartford-East Hartford, CT	Portland-Vancouver-Beaverton, OR-WA
Billings, MT	Hickory-Lenoir-Morganton, NC	Providence-New Bedford-Fall River, RI-MA
Binghamton, NY	Houston-Sugar Land-Baytown, TX	Provo-Orem, UT
Birmingham-Hoover, AL	Huntington-Ashland, WV-KY-OH	Raleigh-Cary, NC
Bismarck, ND	Huntsville, AL	Reading, PA
Blacksburg-Christiansburg-Radford, VA	Indianapolis-Carmel, IN	Reno-Sparks, NV
Boise City-Nampa, ID	Iowa City, IA	Richmond, VA
Boston-Cambridge-Quincy, MA-NH	Jackson, MS	Riverside-San Bernardino-Ontario, CA
Boulder, CO	Jackson, TN	Roanoke, VA
Bowling Green, KY	Jacksonville, FL	Rochester, NY
Bremerton-Silverdale, WA	Janesville, WI	Rockford, IL
Brownsville-Harlingen, TX	Jefferson City, MO	Rocky Mount, NC
Buffalo-Niagara Falls, NY	Joplin, MO	Sacramento–Arden-Arcade–Roseville, CA
Burlington, NC	Kalamazoo-Portage, MI	Saginaw-Saginaw Township North, MI
Burlington-South Burlington, VT	Kankakee-Bradley, IL	Salem, OR
Canton-Massillon, OH	Kansas City, MO-KS	Salinas, CA
Cape Coral-Fort Myers, FL	Kennewick-Pasco-Richland, WA	Salt Lake City, UT
Carson City, NV	Killeen-Temple-Fort Hood, TX	San Antonio, TX
Casper, WY	Kingsport-Bristol-Bristol, TN-VA	San Diego-Carlsbad-San Marcos, CA
Cedar Rapids, IA	Knoxville, TN	San Francisco-San Mateo-Redwood City, CA
Champaign-Urbana, IL	Kokomo, IN	San Jose-Sunnyvale-Santa Clara, CA
Charleston, WV	La Crosse, WI-MN	Santa Fe, NM
Charleston-North Charleston-Summerville, SC	Lafayette, IN	Santa Rosa-Petaluma, CA
Charlotte-Gastonia-Concord, NC-SC	Lafayette, LA	Savannah, GA
Chattanooga, TN-GA	Lake Charles, LA	Scranton–Wilkes-Barre, PA
Chicago-Naperville-Joliet, IL-IN-WI	Lake Havasu City-Kingman, AZ	Seattle-Bellevue-Everett, WA
Chico, CA	Lakeland-Winter Haven, FL	Sherman-Denison, TX
Cincinnati-Middletown, OH-KY-IN	Lancaster, PA	Sioux City, IA-NE-SD
Cleveland-Elyria-Mentor, OH	Lansing-East Lansing, MI	Sioux Falls, SD
College Station-Bryan, TX	Las Vegas-Paradise, NV	South Bend-Mishawaka, IN-MI
Colorado Springs, CO	Lawrence, KS	Spartanburg, SC
Columbia, MO	Lebanon, PA	Spokane, WA
Columbia, SC	Lewiston-Auburn, ME	Springfield, MA
Columbus, GA-AL	Lexington-Fayette, KY	Springfield, MO
Columbus, OH	Lima, OH	Springfield, OH
Corpus Christi, TX	Lincoln, NE	St. Cloud, MN
Corvallis, OR	Little Rock-North Little Rock-Conway, AR	St. George, UT
Dallas-Fort Worth-Arlington, TX	Longview, TX	St. Joseph, MO-KS
Dalton, GA	Los Angeles-Long Beach-Santa Ana, CA	St. Louis, MO-IL
Dayton, OH	Louisville/Jefferson County, KY-IN	Sumter, SC
Decatur, AL	Lubbock, TX	Syracuse, NY
Decatur, IL	Lynchburg, VA	Tampa-St. Petersburg-Clearwater, FL
Denver-Aurora, CO /1	Macon, GA	Toledo, OH
Des Moines-West Des Moines, IA	Madison, WI	Tucson, AZ
Detroit-Warren-Livonia, MI	Manchester-Nashua, NH	Tulsa, OK
Dothan, AL	Manhattan, KS	Tyler, TX
Dover, DE	Mansfield, OH	Utica-Rome, NY
Dubuque, IA	McAllen-Edinburg-Mission, TX	Vineland-Millville-Bridgeton, NJ
Duluth, MN-WI	Medford, OR	Visalia-Porterville, CA
Durham, NC	Memphis, TN-MS-AR	Warner Robins, GA
El Paso, TX	Merced, CA	Waterloo-Cedar Falls, IA
Elkhart-Goshen, IN	Miami-Miami Beach-Kendall, FL	Wausau, WI
Elmira, NY	Midland, MI	Wenatchee, WA
Enid, OK	Milwaukee-Waukesha-West Allis, WI	Wichita Falls, TX
Erie, PA	Mobile, AL	Wichita, KS
Eugene-Springfield, OR	Modesto, CA	Wilmington, NC
Evansville, IN-KY	Monroe, LA	Winston-Salem, NC
Fargo, ND-MN	Montgomery, AL	Worcester, MA
Farmington, NM	Muskegon-Norton Shores, MI	York-Hanover, PA
Fayetteville, NC	Myrtle Beach-North Myrtle Beach-Conway, SC	Youngstown-Warren-Boardman, OH-PA
Fayetteville-Springdale-Rogers, AR-MO	Nashville-Davidson–Murfreesboro–Franklin, TN	Yuma, AZ
Flagstaff, AZ	New Haven-Milford, CT	

Appendix B: Control variables for local HP comovment

The U.S. housing market has been typically characterized by local factors such as differences in income and demographic variables, as well as other localized characteristics that potentially impede interactions among regional housing markets (e.g., Miao et al. 2011). In principle, regional HP is a function of regional housing supply and demand. A quick reading of the existing literature provides a host of determinants of local HP in both demand and supply sides. On the demand side, the literature focuses on the fundamentals of HP determination such as income, population, and interest rates. Showing that contemporaneous local income growth is large enough to account for more than a half of the HP appreciation, Ferreira and Gyourko (2014) claim local income as the only potential demand shifter. Using U.S. city data, Van Nieuwerburgh and Weill (2010) also document that a small increase in (real) wage dispersion generates a large increase in HP dispersion. The authors find that wages account for about 30% of the variation in HPs across regions in both model and data, but they do not link growth in wages and growth in HPs at the individual MSA level. Population growth is also known to proxy the average change in housing demand, with higher average population growth suggesting a higher average demand for new housing (e.g., Hernández-Murillo et al. 2017). Although housing market fundamentals are important in explaining much of the local HP changes, there is no reason to believe that they are responsible for the increased comovement of HP changes. In fact, it is widely documented that HP covaries across locations differently from fundamentals. To be specific, U.S. housing prices have been rising faster than incomes and other prices in virtually every metropolitan area since 1995. Moreover, fundamentals like per capita income or population growths exhibit much less serial correlation in their fluctuations. Using 74 U.S. MSA data, Hwang and Quigley (2006) find a positive, but rather weak, relationship between HP appreciation and income growth. Taken together, it seems logical that conventional fundamentals like income are not much at work in explaining the surge in HP comovements across U.S. MSAs, probably because growing financial integration within the U.S. might have loosened the link between income and HP by reducing borrowing constraints. On the supply side, most studies tend to focus on the impact of housing stock, land supply, and land controls on housing price. There is growing acceptance of explanation that local HPs are highly influenced by local housing market regulations or constraints (e.g., Gyourko et al. 2013, Paciorek 2013). The dynamics of HP is quite different in the cities depending on whether the local housing market is subject to strong or weak regulations. In the literature, two measures of housing market supply constraints are popularly used: (i) a summary measure of the stringency of the local regulatory environment developed by Gyourko et al. (2008), often referred to as the Wharton Residential Land Use Regulation Index (WRLURI); and (ii) the metropolitan-level housing supply elasticity drawn from Saiz (2010). Comprised of 11 sub-indexes that summarize information on the different aspects of the regulatory environment, the WRLURI index is designed so that a low value indicates a less restrictive or more *laissez faire* approach to regulating the local housing market. Incorporating the role of topography to estimate the elasticity of housing supply, Saiz(2010) measures the value of the housing supply elasticity related to both physical and regulatory constraints. A large body of research studies (e.g., Gyourko et al. 2008, Hwang and Quigley 2006) has documented that cities with heavier regulations on the housing market, and hence with a lower elasticity of housing supply, are likely to have faster and more volatile growth of HPs. Intuitively, cities with different levels of housing supply constraints, or different elasticities of housing supply, are likely to have a weaker comovement of city-level HPs.

Geographic proximity also plays an important role in the interactions among regional housing markets because physical distance is often viewed as a salient factor for the spatial distribution of HPs due to the illiquidity and non-transferability feature of housing assets. Since physical distance represents transactions friction, we expect a more disparate, and hence less correlated, movements of HPs between cities that are farther apart. Indeed, there is a great deal of empirical evidence that HPs are more dissimilar for the location pairs which are geographically farther apart (e.g., Miao et al. 2011, Zhu et al. 2013). Zhu et al. (2013) report that the economic closeness is an important driver of the co-movements in HPs across U.S. regions, with stronger comovements in geographically proximate regions. Examining 19 U.S. housing markets, they find that spatial comovements are strong among regions that are less than 250 miles from each other, but become insignificant when the distance is longer than 750 miles.

Overall, while none of these factors alone provide a full accounting of the observed dynamics of intercity HP movements, it is generally believed that fundamentals like income and population interact with housing supply constraints.

Table 1: Summary of selected previous studies on HP comovement

Study	Data	HP	Comovement measure	Driving force
Cotter et al. (2015)	384 U.S. MSAs (1983-2010)	FHFA HPI	R-square	Macro & policy shocks
Del Negro & Otrok (2007)	48 U.S. states (1986-2005)	OFHEO HPI	exposure to common factor	Not monetary integration policy shock
Hirata et al. (2012)	18 OECD countries (1992-2008)	National data from OECD	correlation & concordance	Global interest rate and uncertainty shocks
Kallberg et al. (2014)	14 U.S. MSAs (1992-2008)	Case-Shiller price index	correlation	Systematic real and financial factors
Landier et al. (2017)	50 U.S. states (1976-2000)	OFHEO HPI	correlation	Banking integration

Table 2: Summary statistics

	Full sample			Pre-2000			Post-2000		
Variables	mean	s.d.	90-10 ratio	mean	s.d.	90-10 ratio	mean	s.d.	90-10 ratio
HP ($1,000)	147.2	54.8	1.79	111.9	32.6	1.58	212.7	95.0	2.10
HP growth (%)	0.98	0.23	1.78	0.88	0.24	2.06	0.67	0.31	4.00
Per capita income ($1,000)	23.7	3.6	1.42	15.0	2.1	1.39	35.3	5.8	1.45
Per capita income growth (%)	4.90	0.30	1.16	6.31	0.50	1.20	3.09	0.47	1.48
Population (in million)	808.1	1,698.8	15.00	724.1	1,577.7	15.24	920.1	1,872.4	16.38
Population growth (%)	1.14	0.96	242.00	1.30	1.14	74.5	0.95	0.81	38.90
Per capita deposit ($1,000)	17.5	30.4	2.33	10.5	3.5	2.00	20.0	40.5	2.50
Per capita deposit growth (%)	0.33	0.17	5.41	0.14	0.14	73.06	0.40	0.20	4.99

Note: Full sample period is 1975-2017 except for the financial integration and per capita deposit which are available for the period 1994-2017. '90-10 ratio' represents the ratio of the 90^{th}-percentile city to the 10^{th}-percentile city among 239 cities.

Table 3: Common component share across different numbers of common factor

factor	Full sample			1975-1999			2000-2017		
number	mean	median	[min,max]	mean	median	[min,max]	mean	median	[min,max]
1	0.417	0.428	[0.012, 0.752]	0.287	0.302	[0.000, 0.760]	0.646	0.672	[0.073, 0.925]
2	0.510	0.531	[0.105, 0.791]	0.403	0.413	[0.017, 0.800]	0.735	0.769	[0.187, 0.951]
3	0.575	0.588	[0.110, 0.849]	0.492	0.503	[0.052, 0.856]	0.790	0.824	[0.193, 0.968]
4	0.620	0.634	[0.154, 0.849]	0.554	0.563	[0.143, 0.870]	0.826	0.870	[0.201, 0.974]
5	0.660	0.672	[0.156, 0.879]	0.608	0.627	[0.178, 0.890]	0.843	0.881	[0.251, 0.977]
6	0.697	0.717	[0.168, 0.895]	0.650	0.669	[0.199, 0.904]	0.856	0.888	[0.289, 0.979]
7	0.728	0.751	[0.171, 0.910]	0.686	0.710	[0.233, 0.909]	0.868	0.897	[0.302, 0.980]
8	0.750	0.767	[0.191, 0.910]	0.715	0.739	[0.251, 0.919]	0.878	0.905	[0.382, 0.982]

Note: Entries represent the average and median values of common component share, or the extent to which local HP growth is explained by common national factors, among 239 U.S. MSAs. Entries inside parenthesis denote the minimum and maximum values of common component share. The full sample covers the period of 1975-2017.

Table 4: Impacts of financial integration on (average) HP growth

Dependent variables	Explanatory variables	Out-of-state deposit ratio		co-Herfindahl index	
		Model 1	Model 2	Model 1	Model 2
	Financial integration (1994-2000)	0.0083 (0.0052)	-0.0005 (0.0140)	0.7013 (0.4292)	0.5126 (0.3139)
	Income growth (1975-1994)	-0.1105* (0.0607)	0.0587 (0.0651)	0.0008 (0.1315)	0.0123 (0.1402)
	Population growth (1975-1994)	0.0064‡(0.0012)	-0.0048‡(0.0009)	-0.1691‡(0.0684)	0.0058 (0.0714)
	Deposit growth (1994-2000)	-0.0201 (0.1394)	-0.0174 (0.1436)	0.0061‡(0.0011)	-0.0043‡(0.0006)
Average house	SAIZ	-	-0.0259 (0.0189)		-0.0234‡(0.0191)
price growth	WRLURI	-0.0110 (0.0271)	-	-0.0143 (0.0253)	
(1975-1994)	SAIZ × Financial integration	-	0.0011 (0.0050)		0.0000 (0.0019)
	WRLURI × Financial integration	0.0030 (0.0063)	-	0.0022 (0.0058)	
	Constant	0.0518‡(0.0093)	0.0622‡(0.0098)	0.0495‡(0.0088)	0.0580‡(0.0096)
	[Adjusted R^2]	[0.2582]	[0.2770]	[0.2810]	[0.2896]
	Financial integration (1994-2006)	0.0332‡(0.0046)	0.0656‡(0.0102)	0.5574‡(0.1233)	0.4271‡(0.1431)
	HP growth (1975-1994)	0.4804‡(0.0946)	0.4164‡(0.1065)	0.4940‡(0.0931)	0.4511‡(0.1098)
	Income growth (1995-2006)	0.9835‡(0.1794)	0.9545‡(0.1862)	1.0613‡(0.1996)	1.0389‡(0.1642)
Average house	Population growth (1995-2006)	0.3205‡(0.0917)	0.3307‡(0.0987)	0.2285‡(0.1040)	0.2512‡(0.1139)
price growth	Deposit growth (1995-2006)	-0.0038 (0.0376)	-0.0229 (0.0453)	0.0011 (0.0025)	-0.0037‡(0.0012)
(1995-2006)	SAIZ	-	0.0029‡(0.0014)		-0.0351 (0.0426)
	WRLURI	-0.0015 (0.0020)	-	-0.0516 (0.0499)	
	SAIZ × Financial integration	-	-0.0169‡(0.0038)		0.0023 (0.0022)
	WRLURI × Financial integration	0.0101* (0.0053)	-	0.0049 (0.0056)	
	Constant	-0.0315‡(0.0073)	-0.0318‡(0.0088)	-0.0283‡(0.0079)	-0.0173 (0.0088)
	[Adjusted R^2]	[0.5806]	[0.6169]	[0.5413]	[0.5591]
	Financial integration (2007-2017)	0.0126‡(0.0048)	0.0284‡(0.0116)	0.0599 (0.0943)	0.1049‡(0.1331)
	HP growth (1995-2006)	-0.5765‡(0.0636)	-0.5766‡(0.0823)	-0.4923‡(0.0559)	-0.4859‡(0.0704)
	Income growth (2007-2017)	0.9364‡(0.1587)	1.0273‡(0.1909)	0.9186‡(0.1659)	0.9533‡(0.2078)
Average house	Population growth (2007-2017)	0.8862‡(0.1114)	0.9829‡(0.1309)	0.9226‡(0.1250)	1.0182‡(0.1480)
price growth	Deposit growth (2001-2017)	0.1235‡(0.0430)	0.1096‡(0.0440)	-0.0015 (0.0017)	0.0013‡(0.0008)
(2007-2017)	SAIZ	-	0.0019 (0.0013)		0.1123 (0.0387)
	WRLURI	-0.0027 (0.0018)	-	0.1110‡(0.0429)	
	SAIZ × Financial integration	-	0.0061* (0.0037)		0.0036 (0.0018)
	WRLURI × Financial integration	0.0096‡(0.0039)	-	0.0076†(0.0038)	
	Constant	-0.0102* (0.0053)	-0.0179‡(0.0070)	-0.0076 (0.0056)	-0.0085 (0.0071)
	[Adjusted R^2]	[0.5143]	[0.4763]	[0.4986]	[0.4612]

Note: The regression equation is

$$\Delta\widehat{HP}_{iT} = \alpha + \beta_1 FI_{iT} + \beta_2 SC_i + \beta_3 FI_{iT} \times SC_i + Z_{iT}\gamma + \varepsilon_i, \quad i = 1, ..., N,$$

where $\Delta\widehat{HP}_{iT}(=\frac{1}{T}\sum_{t=1}^{T}\Delta HP_{it})$ is the average growth rate of HP in city i during the period $t = 1, ..., T$. $Z \in \{\Delta\widehat{Inc}_{it}, \Delta\widehat{Pop}_{it}, \Delta\widehat{Dep}_{it}\}$ where Inc_{it}, Pop_{it}, and Dep_{it} respectively denote per capita income, population, and per capita bank deposit in city i at time t. 'Financial integration' denotes the deposit share of the out-of-state banks in each city. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5% and 10% significance levels with the corresponding s.e. inside parentheses.

Table 5: Regression results of the impact on city-pair HP comovements

FI measure	Explanatory variables	Dep. variable	
		Correlation	$\hat{b}_{ij}$
Share of out-of-state bank deposit	Financial integration	0.0868‡(0.0095)	0.1586‡(0.0183)
	Income growth correlation	0.1306‡(0.0055)	0.0317‡(0.0111)
	Population growth correlation	0.1777‡(0.0029)	0.2058‡(0.0054)
	Deposit growth correlation	0.0448‡(0.0034)	0.0261‡(0.0065)
	Difference in WRLURI	-0.0027‡(0.0010)	-0.0042†(0.0020)
	Physical distance	-0.0651‡(0.0012)	-0.0743‡(0.0023)
	State dummy	0.1563‡(0.0040)	0.1471‡(0.0070)
	Constant	0.8210‡(0.0094)	0.9544‡(0.0183)
co-Herfindahl index	Financial integration	0.7451‡(0.0449)	0.7372‡(0.0899)
	Income growth correlation	0.1377‡(0.0054)	0.0413‡(0.0111)
	Population growth correlation	0.1756‡(0.0028)	0.2039‡(0.0054)
	Deposit growth correlation	0.0411‡(0.0034)	0.0262‡(0.0064)
	Difference in WRLURI	-0.0029‡(0.0010)	-0.0039* (0.0020)
	Physical distance	-0.0615‡(0.0011)	-0.0688‡(0.0023)
	State dummy	0.1297‡(0.0045)	0.1243‡(0.0079)

Note: The regression equation is $y_{ij} = \alpha_0+\beta FI_{ij}+X_{ij}\delta+Z_{ij}\gamma+\epsilon_{ij}$ where y_{ij} denotes the bilateral comovement of local HP growths between cities i and j, measured either by the heteroskedasticity-adjusted correlation coefficient (*correlation*) or by the R-square measure of integration ($\hat{b}_{ij}$). FI_{ij} represents the degree of financial integration between cities i and j, proxied by the share of out-of-state bank deposits or by the co-Herfindahl index. X contains conventional fundamental variables of HP determination, such that $X \in \{Corr(\Delta Inc_i, \Delta Inc_j), Corr(\Delta Pop_i, \Delta Pop_j), Corr(\Delta Dep_i, \Delta Dep_j)\}$, where Inc, Pop, and Dep respectively denote per capita income, population, and per capita bank deposits. Z embraces additional local control variables, $Z \in \{SC_{ij}, \log DIST_{ij}, STATEDUM_{ij}\}$. '$SC_{ij}$' denotes the city-pair difference in the housing supply constraint measured by the WRLURI, constructed by $[max(x_i, x_j) - min(x_i, x_j)]/max(x_i, x_j)$ where x_h denotes the WRLURI variable for city h. $DIST_{ij}$ is the physical distance between cities i and j measured by the greater-circle distance or orthodromic distance and $STATEDUM_{ij}$ is a within-state dummy variable which takes on the value of one if cities i and j are in the same state and zero otherwise. Standard errors are clustered at the state-pair level.

Table 6: Regression results of the impact on the change in HP comovements

FI measure	Explanatory variables	Dep. variable (change)	
		Correlation	$\hat{b}_{ij}$
Share of out-of-state bank deposit	Financial integration	-0.2520‡(0.0185)	-0.2929‡(0.0364)
	Change in income growth correlation	0.1314‡(0.0069)	0.0992‡(0.0146)
	Change in population growth correlation	0.1332‡(0.0032)	0.1296‡(0.0063)
	Change in deposit growth correlation	0.0222‡(0.0067)	0.0480‡(0.0132)
	Difference in WRLURI	-0.0234‡(0.0020)	-0.0190‡(0.0039)
	Physical distance	0.0372‡(0.0024)	0.0543‡(0.0043)
	State dummy	-0.4161‡(0.0074)	-0.4413‡(0.0133)
	Constant	0.4723‡(0.0155)	0.3999‡(0.0278)
Co-Herfindahl index	Financial integration	-2.1076‡(0.0905)	-1.7382‡(0.1794)
	Change in income growth correlation	0.1411‡(0.0068)	0.1083‡(0.0146)
	Change in population growth correlation	0.1373‡(0.0032)	0.1331‡(0.0063)
	Change in deposit growth correlation	0.0320‡(0.0067)	0.0515‡(0.0133)
	Difference in WRLURI	-0.0229‡(0.0020)	-0.0185‡(0.0039)
	Physical distance	0.0272‡(0.0023)	0.0440‡(0.0042)
	State dummy	-0.3403‡(0.0085)	-0.3829‡(0.0150)

Note: The regression equation is $\Delta y_{ij} = \alpha + \beta FI_{ij} + \Delta X_{ij}\delta + Z_{ij}\gamma + \varepsilon_{ij}$ where Δy_{ij} denotes the change in the comovement after 2000 such that $\Delta y_{ij} = y_{ij,post} - y_{ij,pre}$ and $y_{ij,post} = Corr(\Delta HP_{i,post}, \Delta HP_{j,post})$ or $y_{ij,post} = \hat{b}_{ij,post}$, and 'pre' and 'post' denote respectively the pre-2000 and post-2000 periods. ΔX_{ij} includes the *changes* in the correlation of per capita income growth, population growth, and per capita deposit growth, between cities i and j after 2000. Refer to the footnote in Table 5 for the descriptions of other variables. Robust standard errors are shown in parentheses. Standard errors are clustered at the state-pair level.

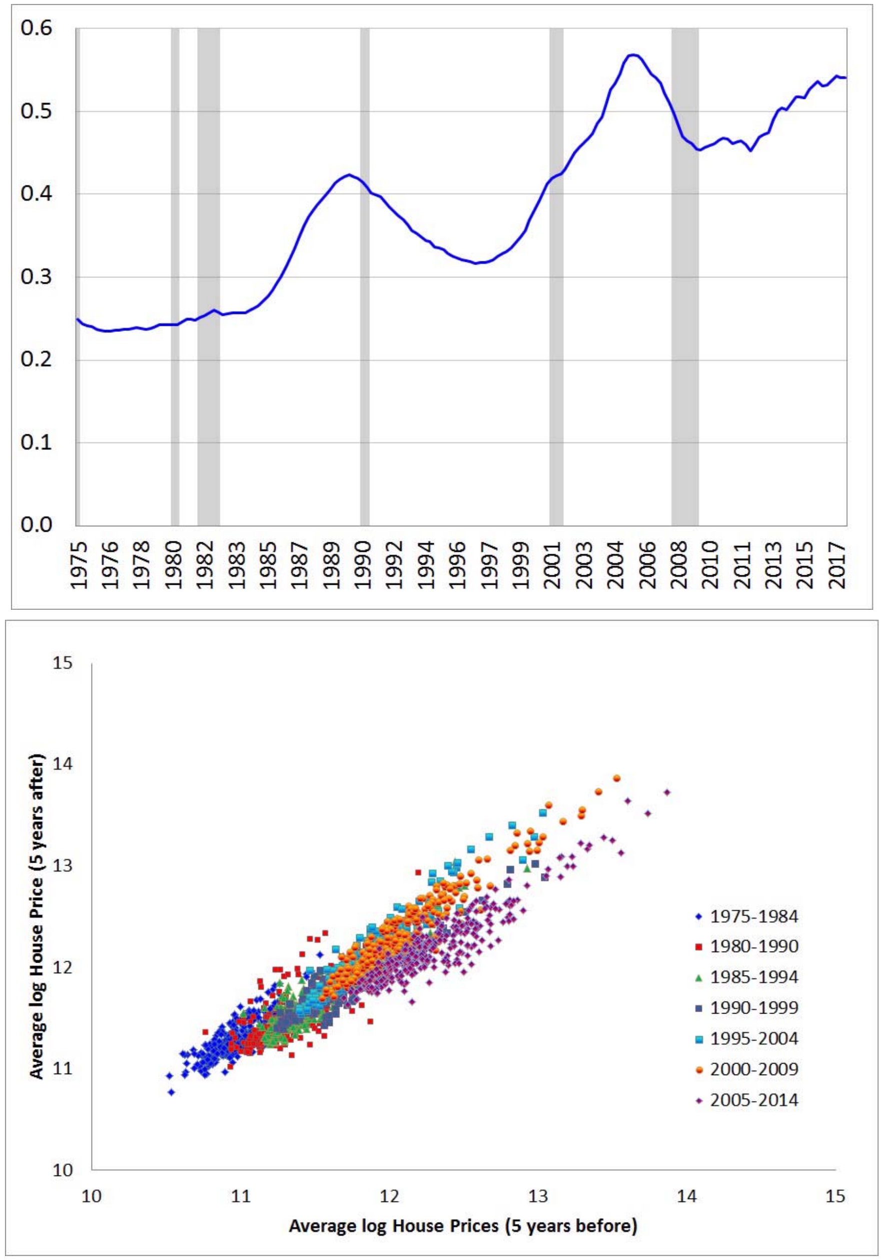

Figure 1: Coefficient of variation (top) and scatterplots (bottom) of MSA house prices

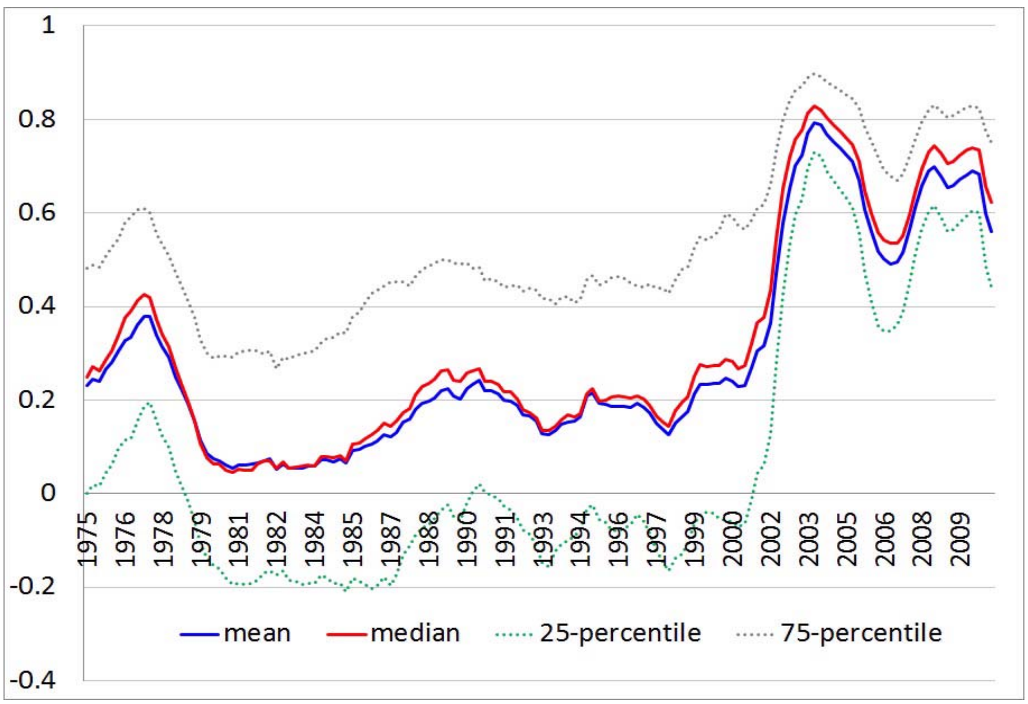

Figure 2: Correlation of house price changes of 256 MSAs for 5-year rolling window

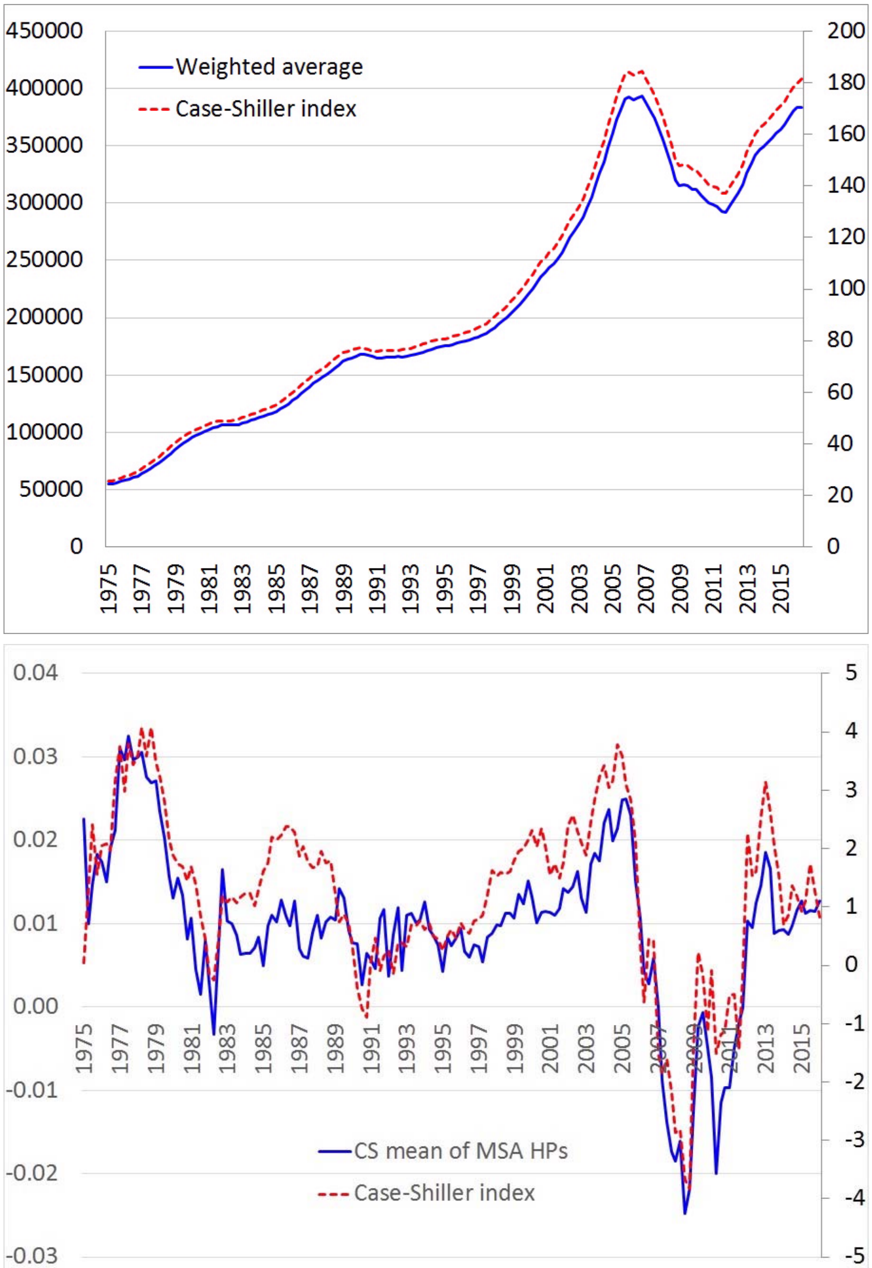

Figure 3: National house prices (top) and house price growth rates (bottom)

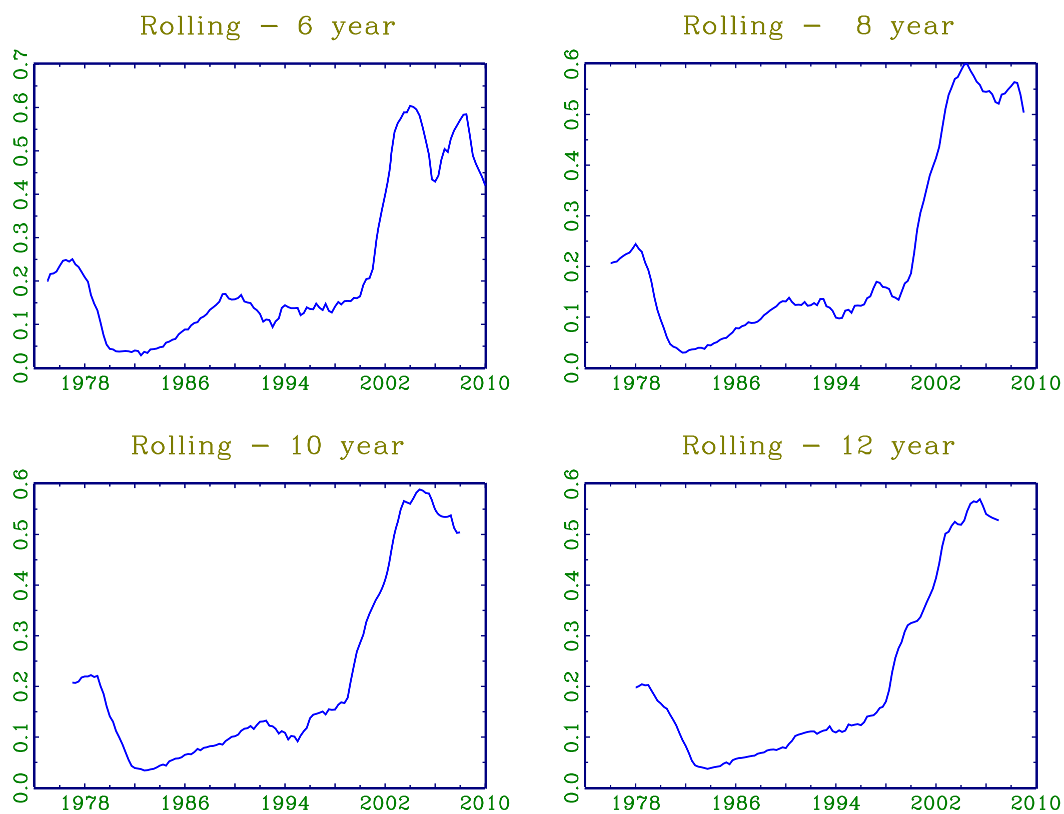

Figure 4: Evolution of the heteroskedasticity-adjusted correlation for various rolling windows

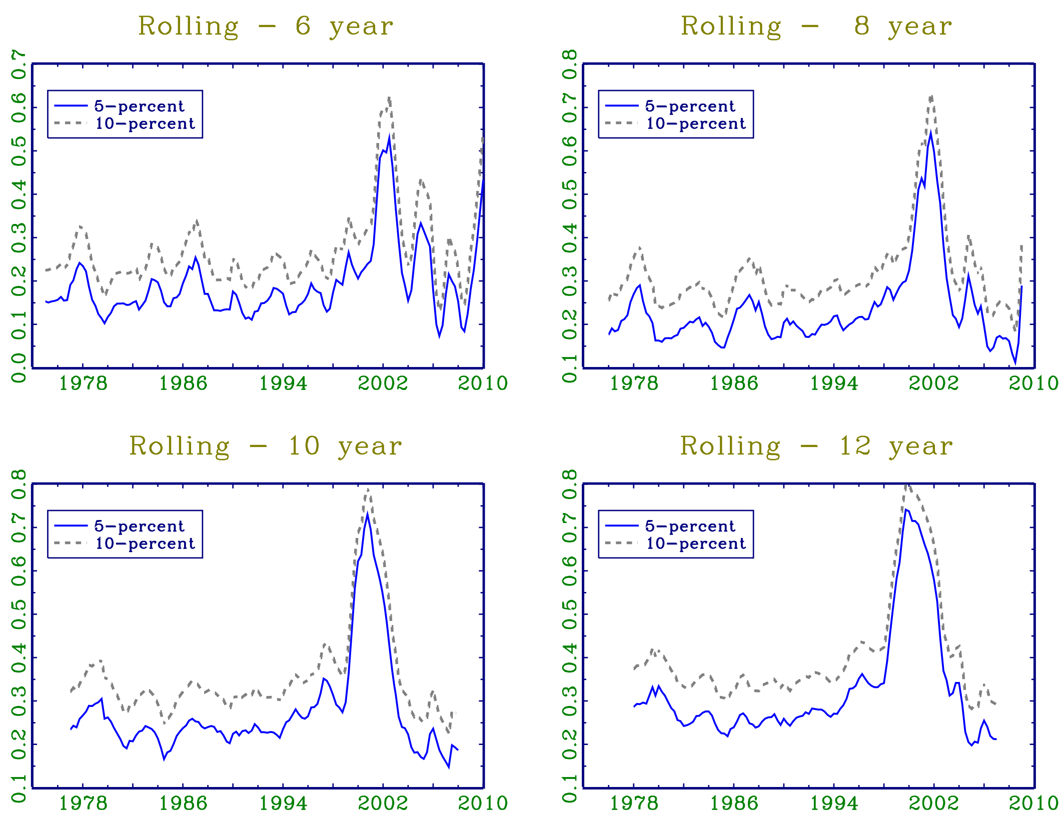

Figure 5: Rejection rate of the null of no change in correlation for various rolling windows

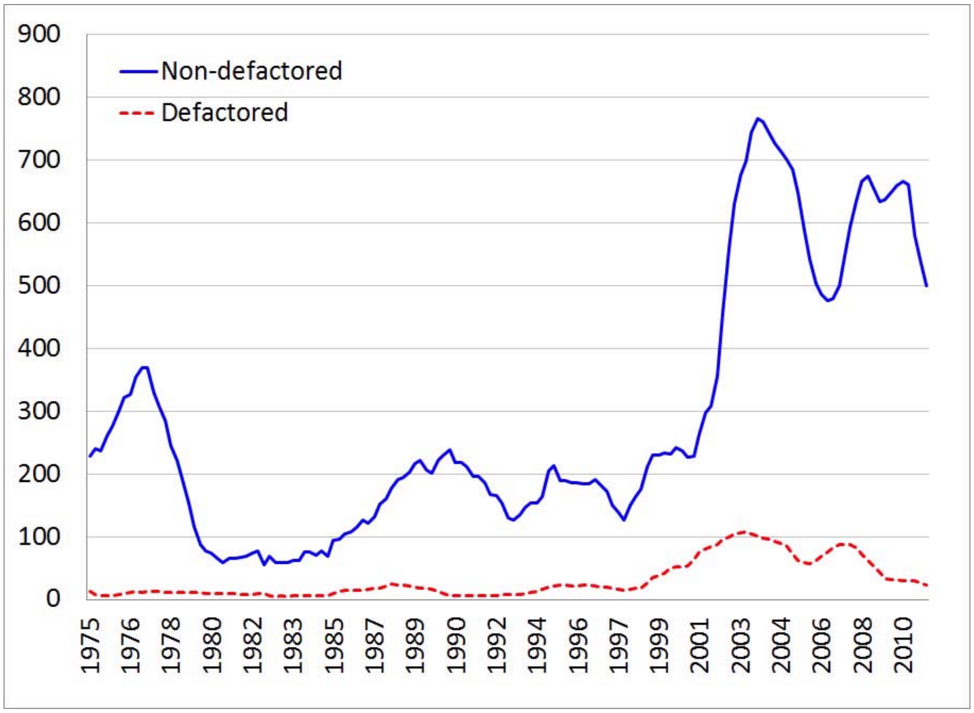

Figure 6: CD-test statistic for non-defactored (solid) and defactored (dotted) house price growth rates

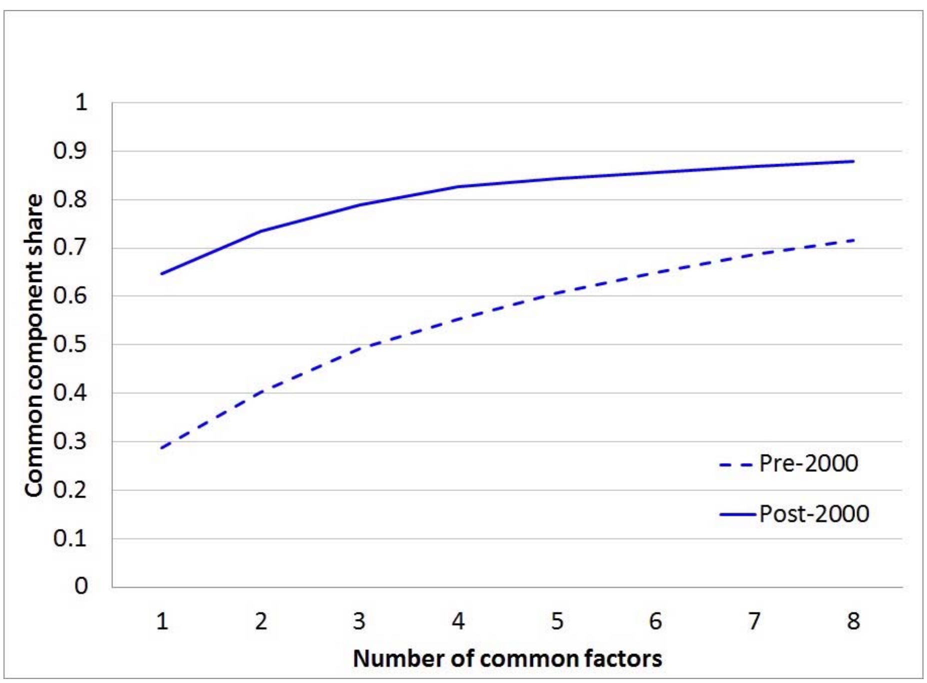

Figure 7: Fraction of variance explained by different numbers of common factors

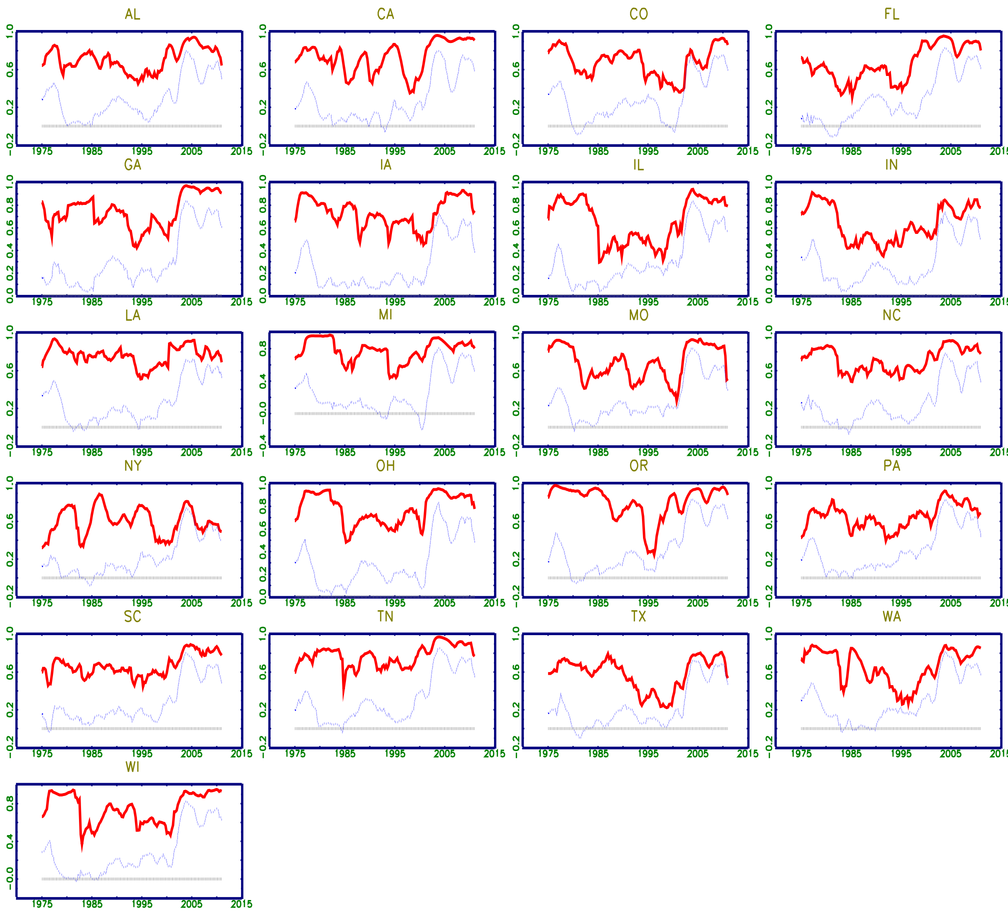

Figure 8: 5-year rolling correlation of house price growth for 21 states

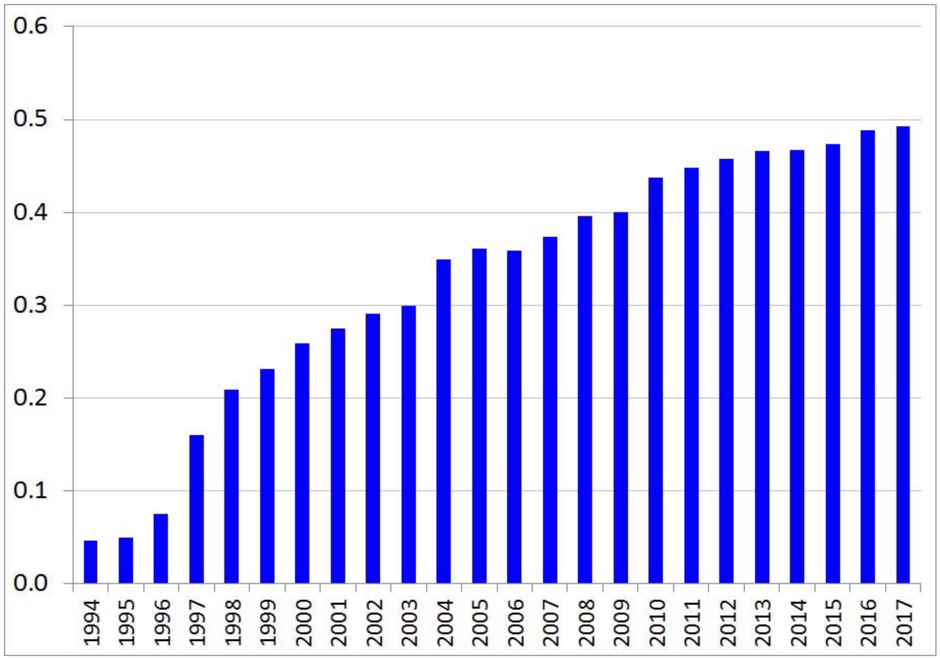

Figure 9: Average share of out-of-state banks deposit over time

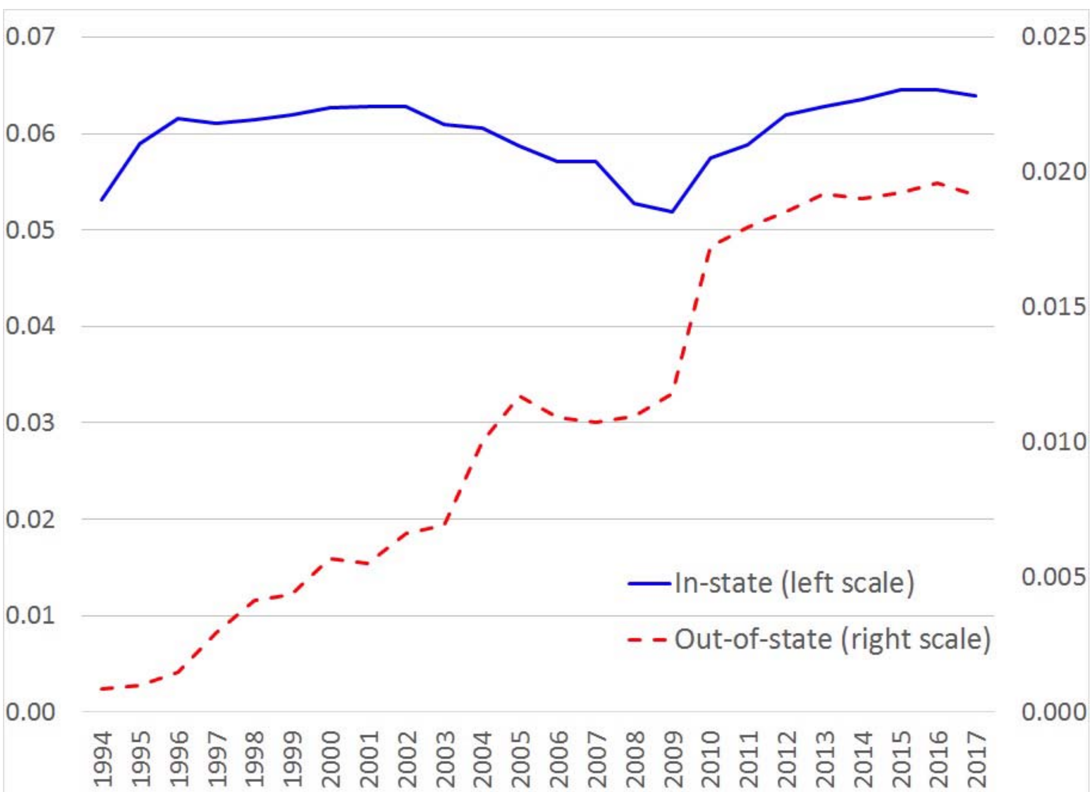

Figure 10: Evolution of average co-Herfindahl index within-state vs. out-of-state city-pairs

Figure 11: Measure of financial integration and pre-1995 correlation (top) correlation change (bottom)

Online Appendix: Robustness check results (not for publications)

Table OA.1: Regression results of the impact on the change in comovement (1995 as a split point)

Explanatory variables	Dep. variable (change)	
	Correlation	$\hat{b}_{ij}$
Financial integration	-1.8372‡(0.0944)	-1.5226‡(0.1769)
Change in income growth correlation	0.1407‡(0.0072)	0.1145‡(0.0144)
Change in population growth correlation	0.1330‡(0.0034)	0.1325‡(0.0063)
Change in deposit growth correlation	0.0465‡(0.0071)	0.0669‡(0.0132)
Difference in WRLURI	-0.0274‡(0.0021)	-0.0222‡(0.0039)
Physical distance	0.0312‡(0.0024)	0.0496‡(0.0042)
State dummy	-0.3545‡(0.0088)	-0.3934‡(0.0152)
Constant	0.4868‡(0.0163)	0.3907‡(0.0282)

Note: The co-Herfindahl index is used as a measure of financial integration. Refer to the note in Table 6.

Table OA.2: Regression results of the impact on the change in comovement (1985-2017)

Explanatory variables	Dep. variable (change)	
	Correlation	$\hat{b}_{ij}$
Financial integration	-2.9605‡(0.0827)	-4.3776‡(0.2054)
Change in income growth correlation	0.1544‡(0.0060)	0.1940‡(0.0173)
Change in population growth correlation	-0.0162‡(0.0028)	-0.0121 (0.0080)
Change in deposit growth correlation	-0.0925‡(0.0059)	-0.0435‡(0.0160)
Difference in WRLURI	0.0197‡(0.0017)	0.0100‡(0.0049)
Physical distance	-0.0279‡(0.0019)	-0.1017‡(0.0051)
State dummy	-0.0454‡(0.0073)	-0.1051‡(0.0175)
Constant	0.5484‡(0.0126)	0.9907‡(0.0334)

Note: The co-Herfindahl index is used as a measure of financial integration. Refer to the note in Table 6.

Table OA.3: Regression results of the impact on the change in comovement (1975-2006)

Explanatory variables	Dep. variable (change)	
	Correlation	$\hat{b}_{ij}$
Financial integration	-0.5387‡(0.1459)	-0.9178‡(0.2493)
Change in income growth correlation	0.0044 (0.0109)	0.0734‡(0.0228)
Change in population growth correlation	0.2251‡(0.0054)	0.2667‡(0.0097)
Change in deposit growth correlation	0.1038‡(0.0110)	0.1125‡(0.0201)
Difference in WRLURI	-0.0322‡(0.0033)	-0.0176‡(0.0061)
Physical distance	0.0556‡(0.0035)	0.1140‡(0.0061)
State dummy	-0.2088‡(0.0140)	-0.1791‡(0.0229)
Constant	-0.1667‡(0.0232)	-0.5029‡(0.0400)

Note: The co-Herfindahl index is used as a measure of financial integration. Refer to the note in Table 6.

Table OA.4: Regression results of the impact on the change in comovement (excluding 'superstar' cities)

Explanatory variables	Dep. variable (change)	
	Correlation	$\hat{b}_{ij}$
Financial integration	-2.3263‡(0.1014)	-1.4277‡(0.2002)
Change in income growth correlation	0.1285‡(0.0072)	0.0892‡(0.0157)
Change in population growth correlation	0.1424‡(0.0035)	0.1240‡(0.0069)
Change in deposit growth correlation	0.0236‡(0.0072)	0.0354‡(0.0144)
Difference in WRLURI	-0.0203‡(0.0022)	-0.0148‡(0.0044)
Physical distance	0.0316‡(0.0025)	0.0676‡(0.0047)
State dummy	-0.3388‡(0.0088)	-0.3928‡(0.0154)
Constant	0.5105‡(0.0167)	0.3082‡(0.0313)

Note: The co-Herfindahl index is used as a measure of financial integration. Refer to the note in Table 6.