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Variations and Influences of Connectedness among US Housing Markets

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This paper uses the house price indices of 20 metropolitan statistical areas (MSAs) across the United States from January 1991 to April 2018 to analyze the dynamic connectedness of the housing markets in these MSAs. By estimating the connectedness of the entire sample before, during, and after the subprime mortgage crisis, this paper compares the changes in the impact of each regional housing market in the abovementioned MSAs during the stated time period. The results show that housing markets in west coast MSAs are the most influential, and the spatial distribution of this influence is affected by the subprime mortgage crisis because, compared to other periods, the fewest MSAs have a positive net impact during the crisis period and are found along the coast. The influence of the west coast cities increases after the subprime mortgage crisis compared to that before the crisis, probably because the house prices in these cities recover more quickly. In addition, an increase in connectedness represents more systematic risks and also influences the connectedness of the housing markets with other financial markets. The results of this paper also indicate that if the Federal Reserve uses monetary policies to interfere with the housing market, this might increase the default risks of the entire housing market across the United States, and a financial crisis from the spread of default risks might ensue. By discussing the linkage of the regional housing markets across the United States, we provide another warning indicator for the risks of housing markets, risks linked to other financial markets, and uncertainty risks for the overall economy.

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Keywords

US Housing Markets; Connectedness; Default Risk; Subprime Mortgage Crisis; Housing Market Risk

1. Introduction

Globalization and growth in the speed of the dissemination of all types of information have resulted in rapid changes in cross-country and cross-asset interconnectivity. However, measures of connectedness have long been a central problem of asset management because they represent the need for diversified investments and level of systematic risks. For example, Billio et al. (2012) propose several econometric measures of connectedness based on a principal-component analysis and Granger-causality networks to discuss the level of systemic risk in the finance and insurance industries. Cross-country and cross-asset interconnectivity signify the systematic risks of the global economy; when they change rapidly, investors urgently require a method to dynamically and promptly measure the connections among markets. Diebold and Yilmaz (2014) propose a novel method that can quantify connectedness and verify the size of the net market impact. Most importantly, the method can illustrate changes in dynamic connectedness. This study adopts the method proposed by Diebold and Yilmaz (2014) by using data on the house price indices of 20 metropolitan areas across the United States (U.S.) from January 1991 to April 2018 to analyze the dynamic connectedness of these cities.

The following questions are discussed in this study through the measure of dynamic connectedness: (1) What is the connectedness of the housing markets in the U.S. metropolitan areas? (2) Which cities have a greater impact? (3) How is the subprime mortgage crisis related to the connectedness of regional housing markets? The U.S. economy has recovered from the subprime mortgage crisis that occurred more than 10 years ago. Different indexes (e.g., the S&P 500 and Nasdaq Index) saw historical all-time highs in the first half of 2018. Nonetheless, investors and policy makers must not ignore the potential crises that emerge from risks in the housing market. To prevent similar mortgage crises, this study extensively analyzes the impact of the housing market in 20 metropolitan statistical areas (MSAs) across the U.S. Furthermore, changes before, during, and after the subprime mortgage crisis reflect the influence of connectedness in these housing markets.

The occurrence of the subprime mortgage crisis highlights the importance of two research topics: identifying the systematic risks in the housing market and understanding the effects of the housing market on other markets as well as the overall economy. Regarding the first research topic, systematic risks are identified by estimating the correlation among regional housing markets. The general correlation among regional housing markets (i.e., not during the subprime mortgage crisis) is theoretically explained in the relevant literature (Meen, 1999) and empirically verified to exist in housing markets in MSAs across the U.S. (Gupta and Miller, 2012a; Kallberg et al., 2014). However, research on the dynamic and real-time measurements of the connectedness of housing markets in these MSAs is scant. Most studies concentrate on explaining the average correlation among the markets for all data periods (Gupta and Miller, 2012b)[1] or examining whether such a correlation exhibits structural breaks to describe changes in connectedness during a period of time (Kallberg et al., 2014)[2]. Crises in the housing market cannot be promptly identified merely by estimating systematic risks under general circumstances because the U.S. has experienced a financial crisis that resulted from real estate risks (the subprime mortgage crisis). Thus, this paper aims to obtain quantified and dynamic connectedness, which can be used to comprehensively analyze changes in the connectedness of housing markets in MSAs across the U.S. and discuss other relevant issues, such as the dynamic effects of systematic risks during the subprime mortgage crisis and increased connectedness of housing markets in MSAs.

Regarding the second research topic on the effects of the housing market on other markets and the overall economy, this paper investigates whether the connectedness of regional housing markets influences information dissemination in housing markets to other markets and the overall economy. The subprime mortgage crisis reveals the spread of risks in housing markets to other markets. However, this topic has long been overlooked, because relevant studies focus on discussing the wealth effects between housing markets and stock markets (e.g., Green, 2002) or assert that housing markets and other markets are segmented (e.g., Liu et al., 1990; Ong, 1995). A few studies maintain that the flow of funds from stock markets to housing markets is probably attributable to investment safety requirements (e.g., Tsai, Lee, and Chiang, 2012). Regarding topics on risks in housing markets, this paper will discuss whether the high systematic risk of a housing market spills over to other markets, thereby increasing the connectedness between housing markets and other markets.

In summary, the objective of this paper is to investigate changes in the connectedness of housing markets in MSAs across the U.S. as well as the effects

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[1]Gupta and Miller (2012b) obtain house price indices for the Los Angeles, Las Vegas, and Phoenix metropolitan areas from the Freddie Mac database. Granger causality tests on all samples show that Los Angeles house prices directly affect Las Vegas house prices and indirectly affect Phoenix house prices through their effect on Las Vegas house prices.
[2]Kallberg et al. (2014) analyze the comovement among the Case–Shiller Home Price Indices for 14 metropolitan areas in the U.S. between 1992 and 2008. Their results show that comovement among home price indices considerably increased over the sample period, especially in the late 1990s. Kallberg et al. (2014) assert that comovement among home prices in these cities is attributable to the integration of the economy and financial markets at the time.

of these changes. The results of this study provide a warning indicator for the risks of housing markets, risks linked to other financial markets, and uncertainty risks for the overall economy.

2. Literature Review

2.1 Correlation among Housing Markets in MSAs across the U.S.

Relevant studies mostly investigate the correlation among the housing markets across the U.S. Several verify that real estate markets in certain states are significantly correlated (e.g., Apergis and Payne, 2012; Kim and Rous, 2012; Kuethe and Pede, 2011), whereas others do not support the long-term convergence and spillover effects in U.S. state housing prices (e.g., Barros et al., 2012). Nevertheless, the correlation among housing markets in various MSAs across the U.S. is generally supported by empirical evidence.

Using the Case–Shiller Home Price Indices, Miao et al. (2011) analyze the return and volatility in U.S. housing markets across 16 metropolitan areas for the period of January 1989–June 2006 to observe market dependencies. They separate the research period into two phases—the calm phase (1989–1998) and active-growing phase (1999–2006) of the real estate market—to verify and compare the results in both phases. Their results indicate that New York, San Francisco, and Miami are the most influential markets in terms of the return spillover effect, whereas markets in the central and mountain regions are relatively independent. However, the linkages among these markets are intense during the active phase of the real estate market (1999–2006). The results in Miao et al. (2011) indicate the influential role of housing markets in metropolitan areas along the coasts of the U.S. Using the correlation among regional housing markets, Gupta and Miller (2012a) find predictability of house prices in these metropolitan areas along the coasts of the U.S. They examine the time-series properties of house prices in eight metropolitan areas in southern California, using data from the Freddie Mac House Price Index, which encompass the fourth quarter of 1977 through to the second quarter of 2008. First, they conduct a test for co-integration and find the presence of seven co-integrating vectors, which indicates the significant correlation among these housing markets. When generating out-of-sample forecasts of housing markets in each metropolitan area, Gupta and Miller (2012a) find that the empirical model performs more favorably when forecasting coastal metropolitan areas than inland metropolitan areas.

Canarella et al. (2012) use the Case–Shiller 10-City Home Price Index for the period of January 1987–April 2009 to investigate price dynamics and the ripple effect of house prices following the approach outlined by Meen (1999). They find that house price changes in east and west coast metropolitan areas likely influence other housing markets in the U.S. Furthermore, they find that structural breaks are present in house price dynamics following the housing bubble in the early 1990s and subprime mortgage crisis in the early 2010s. In addition, Pijnenburg (2017) uses house price indices from the Federal Housing Finance Agency that span from the second quarter of 2004 through to the second quarter of 2009, as well as economic variables of 319 U.S. cities. Estimation results show the spillover effect of neighboring house price changes, particularly in times of increasing house prices. The spillover effect decreases during times of declining house prices because of the disposition effect.

In the aforementioned literature, the results of Miao et al. (2011) and Canarella et al. (2012) suggest that structural breaks are found in the correlation among housing markets in metropolitan areas. The results of Miao et al. (2011) and Pijnenburg (2017) indicate that housing markets in metropolitan areas are correlated, particularly when housing markets perform well. Several studies identify increased correlation among housing prices following a subprime mortgage crisis. For example, Cohen et al. (2016) use house price indices published by the Office of Federal Housing Enterprise Oversight for 363 U.S. cities from the first quarter of 1975 until the first quarter of 2013, to construct a contiguity matrix that captures the spatial effects across each city by adding weights to house price growth rates based on the distance between cities and neighboring cities. They find that spatial effects have significant explanatory power in explaining the house price growth rate. Cohen et al. (2016) further analyze post-2007 samples, and their results indicate increased house price contagion across markets after the subprime mortgage crisis.

Therefore, a correlation among the housing markets in MSAs across the U.S. clearly exists. Other studies have mostly proposed the spillover effects of house prices in coastal metropolitan areas. In addition, structural breaks are found in the correlation among housing markets in MSAs, and these changes are probably related to housing market performance and the subprime mortgage crisis.

2.2 Relationship between U.S. Housing Markets with Other Markets and Overall Economy

The performance of a housing market substantially affects the economy of a country because house prices account for a considerable portion of wealth. Calomiris et al. (2013) use U.S. data for the period of 1981–2009 with total retail sales from each state, housing values, and share values as proxies for consumption, housing wealth, and shared wealth, respectively. Their results show a significant housing wealth effect (i.e., the positive effect of rising housing values on consumption). In contrast to the findings of Buiter (2008) and Sinai and Souleles (2005), Calomiris et al. (2013) find that the housing wealth effect is substantially higher than the shared wealth effect. Using the data of 51 U.S. states for the first quarter of 1978 through to the fourth quarter of 2012, Ashley and Li (2014) also verify that housing wealth, compared to shared wealth, exerts a stronger influence on consumption.

Iacoviello and Neri (2010) study the origins and consequences of fluctuations in the U.S. housing market and propose that housing market spillovers to the overall economy are non-negligible and have become more critical over time. Fratzscher et al. (2010) analyze the role of asset prices as a driver of the US trade balance, and find that equity market and housing price shocks have been major determinants of the US current account in the past. Nyakabawo et al. (2015) examine the causal relationships between the real house price index and real GDP per capita in the U.S. Using quarterly time-series data from 1963 to 2012, the results of Nyakabawo et al. (2015) suggest the existence of a unidirectional causality that runs from the real house price index to real GDP per capita, and while the real house price leads real GDP per capita, in general (both during expansions and recessions), significant feedback is also present from real GDP per capita to the real house price.

The aforementioned studies elaborate on the effects that housing markets have on the overall economy and policies, but earlier studies mostly concentrate on delineating the influence of monetary policies on housing markets. For example, Vargas-Silva (2008) studies the impact of monetary policy shocks on U.S. housing markets and finds that housing starts and residential investment respond negatively to contractionary monetary policy shocks. By contrast, recent studies discuss the effects of housing market performance on monetary policies and whether the Federal Reserve uses monetary policies to interfere with housing markets. For example, Simo-Kengne et al. (2016) investigate whether changes in the monetary transmission process as captured by the interest rate respond to variations in asset returns, and by using annual data on the U.S. that span the period of 1890 to 2013, find that the interest rate responds more strongly to asset returns during bull regimes. In addition, while a larger interest-rate effect of stock-return shocks was found prior to the 1970', the interest rate appears to respond more strongly to housing-return than stock return shocks after the 1970s. Aastveit et al. (2017) use a structural vector autoregression (VAR) model to investigate whether the Federal Reserve has responded systematically to asset prices and whether this response has changed over time, and provide evidence which shows that real house price growth influences the monetary policy in the U.S.

Moreover, there are studies in the literature that show in the short run, housing markets might spread risk to other markets. For example, Bahmani-Oskooee and Ghodsi (2018) claim that the housing market crash in 2008 and the impacts on the stock market and American economy show a causal relationship from the housing market to stock market. They test this hypothesis with the use of data at the state level, and find that there is a symmetric causal relationship in the short run from stock to house prices in 10 U.S. states and from house to stock prices in 20 states.

Antonakakis et al. (2016) examine dynamic spillovers among the housing and stock markets, and economic policy uncertainty in the U.S. They use monthly data over the period of 1987M1–2014M11. They find that there are substantial differences in spillovers over time. The spillovers were more pronounced during the global financial crisis in comparison to other historical events. Their results show contagion from the housing and financial crises on the real economy and the strong policy that were enacted to stabilize the economy. Damianov and Elsayed (2018) examine U.S. market monthly returns from January 1975 to December 2016. They find large differences in spillovers among four markets: housing, mortgage and equity real estate investment trust, and stock. Usually the housing market transfers spillovers when the economy is in a downturn but Damianov and Elsayed (2018) find that it received spillovers during the recent economic crisis.

This literature review verifies that risks in housing markets are possibly contagious during an economic recession. Therefore, this paper examines the amount of systematic risks in regional housing markets when housing markets become risk transmitters. The purpose is to understand whether the systematic risks of housing markets spill over to other markets as well as understand the effects of these risks on the overall economy.

3. Estimation of Connectedness

This paper follows the approach to connectedness in Diebold and Yilmaz (2014). First, a VAR model is established with 20 stationary variables to estimate the housing market returns, and the model can be written as a moving average representation expressed as:

$$R_t = \sum_{i=1}^{\infty} \delta_i \varepsilon_{t-i} \tag{1}$$

where the vector R_t represents the housing market returns of twenty cities, and δ is the coefficient matrix and ε is the residual matrix. By applying variance decomposition, we obtain the orthogonal shocks, which is assumed to follow an N-dimensional covariance-stationary data-generating process: $\theta(L)\varepsilon_t$, $\theta(L) = \theta_0 + \theta_1 L + \theta_2 L^2 + \cdots$, $E(\varepsilon_t \varepsilon_t') = I$. Contemporaneous aspects of connectedness are summarized in θ_0 , which need not be diagonal. The dynamic aspects of connectedness are summarized in $\{\theta_1, \theta_2, \ldots\}$

Based on the generalized variance decomposition framework of Koop et al. (1996), Pesaran and Shin (1998), and Del Negro and Schorfheide (2011), Diebold and Yilmaz (2014) find that total connectedness is robust to the ordering of the variables in the VAR model. Let d_{ij}^{gH} denote the ij-th generalized H-step variance decomposition component; that is, the fraction of the H-step forecast error variance of variable I due to shocks in variable j. Then the generalized H-step variance decomposition matrix $D^{gH} = \left[d_{ij}^{gH} \right]$ has the entries:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i ' \delta_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i ' \delta_h \Sigma \delta_h ' e_i \right)} \tag{2}$$

where Σ is the variance matrix for the error vector, that is, the covariance matrix of the shock vector in the non-orthogonalized VAR. σ_{jj} is the standard deviation of the error term for the jth equation. e_i is a selection vector with jth element unity and zero elsewhere, δ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR. The forecast error variance (d_{ij}^{gH}) is obtained and represents the impact of the influence from City i on the housing market returns in City j. In addition, each entry of the variance decomposition matrix is normalized by the row sum in order to calculate the spillover index. Hence, by estimating $D^g = \left[d_{ij}^{gH} \right]$, the generalized connectedness measures can be determined. d_{ij}^{gH} provides the information of the influence of City j on City i, that is $d_{i \leftarrow j}^{gH}$, for various j. The table that contains the estimated results of D^g is "the connectedness table", which shows the disaggregated connectedness measures and aggregate them in various ways to obtain total directional and total connectedness measures.

4. Empirical Results

4.1 Connectedness of Regional Housing Markets

The housing data used in this paper are obtained from the S&P/Case–Shiller Home Price Indices. Seasonally adjusted monthly house price indices for the MSAs as measured by the S&P/Case–Shiller HPI Composite 20 are adopted. Figure 1 shows a list of the 20 MSAs and their approximate geographical location. This paper uses data from January 1991 to April 2018[3].

[3] The house price indices of Dallas are current from January 2000 because data compilation began in 2000.

Figure 1 Map of MSAs

Note: 1 to 20 denote Phoenix, Los Angeles, San Diego, San Francisco, Denver, Washington, Miami, Tampa, Atlanta, Chicago, Boston, Detroit, Minneapolis, Charlotte, Las Vegas, New York, Cleveland, Portland, Dallas, and Seattle, respectively.

Figure 2 plots the house price indices of the 20 MSAs. The graph shows that although most of the house price indices consistently fluctuate (i.e., peaking in the first half of 2006 and declining thereafter until the first half of 2009), the extent of fluctuations in house prices for different MSAs considerably differs, particularly for coastal MSAs such as both Los Angeles and Miami where peak house price indices in 2006 exceed 250 until May 2009, when they drop by more than 40% to approximately 160 and 145 in Los Angeles and Miami, respectively. By comparison, inland cities such as Denver register only an 11.5% decline during the same period. In addition, the majority of the cities project peak house prices in April 2018, thus suggesting that the housing market of these cities has already recovered from the subprime mortgage crisis. In other cities such as Detroit, house prices fluctuate relatively more constantly compared with other cities but recover more slowly, with house price indices not even returning to the highest level before the subprime mortgage crisis.

Figure 2 Housing Price Indices of MSAs

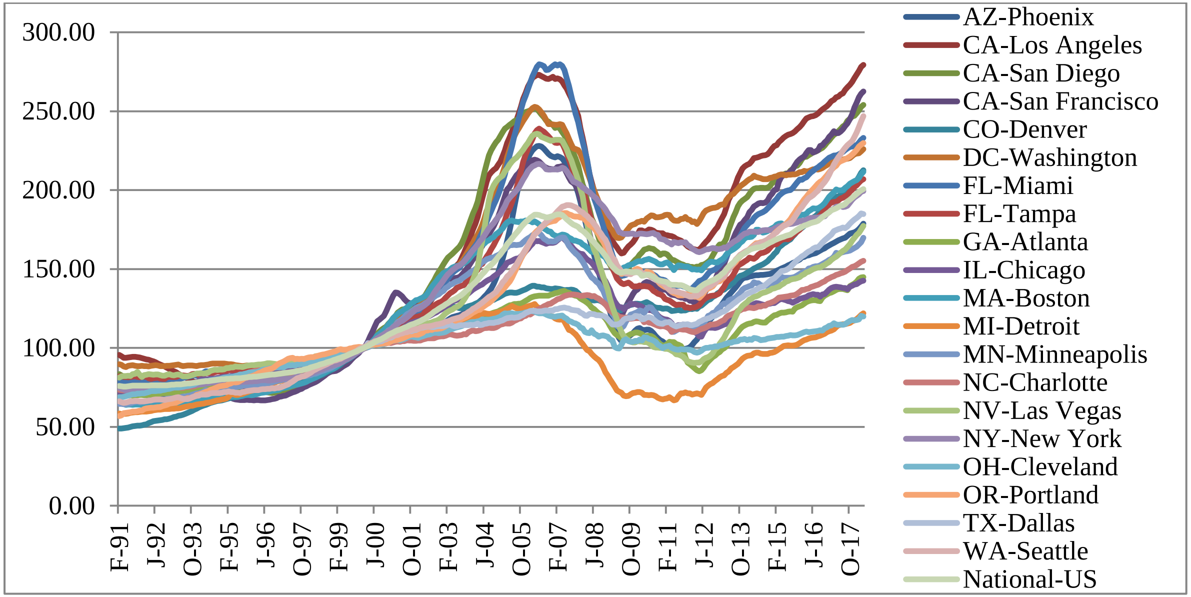


Table 1 presents the simple statistics of house price index returns (hereafter referred to as “housing returns”). In terms of the means, the housing markets in three MSAs in California (Los Angeles, San Diego, and San Francisco) perform the most favorably. In terms of the standard deviation, Las Vegas projects the highest fluctuation return, thus indicating that the housing markets in these three MSAs show high average returns, but their risk of fluctuation is not any higher than that of the other areas. Table 2 shows the unit root test results of the housing returns for the 20 MSAs. These returns are stationary data that can be used to estimate the VAR model.

Table 1 Descriptive Statistics

Statistics	R1	R2	R3	R4	R5
Mean	0.0027	0.0047	0.0042	0.0043	0.0034
Median	0.0045	0.0064	0.0058	0.0058	0.0040
Maximum	0.0423	0.0316	0.0326	0.0302	0.0171
Minimum	-0.0461	-0.0376	-0.0343	-0.0426	-0.0162
Std. Dev.	0.0151	0.0120	0.0119	0.0140	0.0055
Skewness	-0.8326	-0.9916	-0.7420	-0.8949	-0.5056
Kurtosis	4.9357	4.4624	4.0011	4.1252	3.7099
Statistics	R6	R7	R8	R9	R10
Mean	0.0037	0.0039	0.0033	0.0017	0.0016
Median	0.0041	0.0063	0.0052	0.0031	0.0037
Maximum	0.0266	0.0292	0.0288	0.0237	0.0270
Minimum	-0.0215	-0.0423	-0.0342	-0.0495	-0.0337
Std. Dev.	0.0094	0.0129	0.0113	0.0091	0.0083
Skewness	-0.5361	-1.2635	-0.7789	-1.3538	-0.7968
Kurtosis	3.2716	4.6917	3.8070	8.1458	4.2790
Statistics	R11	R12	R13	R14	R15
Mean	0.0034	0.0009	0.0024	0.0020	0.0026
Median	0.0040	0.0032	0.0048	0.0030	0.0046
Maximum	0.0188	0.0334	0.0253	0.0147	0.0531
Minimum	-0.0166	-0.0374	-0.0486	-0.0189	-0.0475
Std. Dev.	0.0068	0.0110	0.0103	0.0052	0.0158
Skewness	-0.2962	-0.7180	-1.5173	-1.0178	-0.4335
Kurtosis	2.7996	4.7172	7.0330	5.0984	5.1507
Statistics	R16	R17	R18	R19	R20
Mean	0.0031	0.0008	0.0038	0.0028	0.0041
Median	0.0026	0.0019	0.0052	0.0030	0.0056
Maximum	0.0178	0.0253	0.0224	0.0229	0.0184
Minimum	-0.0177	-0.0397	-0.0199	-0.0156	-0.0274
Std. Dev.	0.0071	0.0069	0.0080	0.0053	0.0079
Skewness	-0.3616	-0.9108	-0.7355	-0.5933	-1.0731
Kurtosis	2.7000	9.3336	3.6818	4.7270	4.6195

Note: 1 to 20 denote Phoenix, Los Angeles, San Diego, San Francisco, Denver, Washington, Miami, Tampa, Atlanta, Chicago, Boston, Detroit, Minneapolis, Charlotte, Las Vegas, New York, Cleveland, Portland, Dallas, and Seattle, respectively.

Table 2 Unit Root Tests

Test	R1	R2	R3	R4	R5
ADF	-3.3697	-2.6353	-2.3666	-3.3414	-2.5165
p-value	0.0008	0.0083	0.0176	0.0009	0.0117
PP	-2.9932	-2.9674	-3.3987	-4.2115	-4.1870
p-value	0.0028	0.0031	0.0007	0.0000	0.0000
Test	R6	R7	R8	R9	R10
ADF	-2.7550	-2.3520	-2.5258	-5.9168	-4.3094
p-value	0.0059	0.0183	0.0114	0.0000	0.0000
PP	-3.9345	-3.2436	-4.7805	-5.9596	-7.0484
p-value	0.0001	0.0012	0.0000	0.0000	0.0000
Test	R11	R12	R13	R14	R15
ADF	-1.7511	-3.4394	-4.9421	-2.9199	-3.0612
p-value	0.0759	0.0006	0.0000	0.0035	0.0023
PP	-5.8115	-6.7838	-7.8621	-11.2581	-3.8826
p-value	0.0000	0.0000	0.0000	0.0000	0.0001
Test	R16	R17	R18	R19	R20
ADF	-2.1799	-2.3155	-2.5811	-3.8454	-2.3171
p-value	0.0284	0.0201	0.0098	0.0001	0.0200
PP	-4.2970	-12.2354	-5.7613	-7.3305	-4.8603
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Note: 1 to 20 denote Phoenix, Los Angeles, San Diego, San Francisco, Denver, Washington, Miami, Tampa, Atlanta, Chicago, Boston, Detroit, Minneapolis, Charlotte, Las Vegas, New York, Cleveland, Portland, Dallas, and Seattle, respectively. ADF and PP tests are used to test the null hypothesis of a unit root in the series. Intercept is included in the testing equation, and the lag lengths of the unit root models are selected by using a Schwarz information criterion.

Before estimating the dynamic connectedness, we first use an indicator that has been conventionally used for estimating correlations between markets. The correlation coefficients between the housing returns of the 20 MSAs are obtained and listed in Table 3. However, the information provided by such estimation results is limited. First, the direction of mutual influence between markets cannot be identified; only one correlation coefficient exists between any two cities. For example, the correlation coefficient between Phoenix and Los Angeles in this study is 0.81. Second, the autocorrelation coefficient is 1, thus indicating that it can not be used to determine whether the variation in the housing return is due to the housing market of the city in question or the factors of the other cities. For these two limitations, we use a connectedness table to enhance the analysis.

Table 4 is the connectedness table, which shows the interactions among housing market returns, or in other words, the percentage of housing market returns in MSA j (d_{ij}^{gH}) that can be explained by MSA i. Each number in the table represents the effects of the vertical MSAs on their corresponding horizontal MSAs. In addition, the diagonal numbers in Table 4, represent the part where the house market return is subjected to self-influence (d_{ii}^{gH}). A comparison between Tables 3 and 4 reveals that even though the correlation coefficient between Phoenix and Los Angeles is high (0.81), this correlation is primarily derived from the effect of Los Angeles on Phoenix. This is because the correlation percentage that Phoenix is affected by Los Angeles is 11.3%, whereas the correlation percentage that Los Angeles is affected by Phoenix is only 4%. Thus, the net effect of Los Angeles on Phoenix is 7.3%. This result indicates that Los Angeles is a leading city, and we should pay close attention to its housing market changes because they may easily entail changes in the housing markets of other cities and thus represent a systematic risk.

Table 4 shows the correlation between any two MSAs. The highest correlation is observed between the effects of Los Angeles on San Diego and Los Angeles on Las Vegas. The variance of housing returns in Denver is most affected by its own factors. The results presented in Table 4 are in line with previous studies, which show that the housing markets in coastal MSAs (e.g., Los Angeles) are more influential, whereas those in inland MSAs (e.g., Denver) are more independent compared with the other areas.

In Table 4, the rightmost column (labeled *From*) represents the sum of the influence of the other MSAs on each MSA ($C_{i\leftarrow\bullet}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{gH}$), and the bottommost row (labeled *To*) represents the sum of the influence of each MSA on the other MSAs ($C_{\bullet\to j}^{H} = \sum_{\substack{i=1 \\ i\neq j}}^{N} d_{ij}^{gH}$). Following Diebold and Yilmaz (2014), we calculate the *Net* total directional connectedness as $C_i^H = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow\bullet}^{H}$. To facilitate a comparison, Figure 3 shows three total directional connectedness measures (*From*, *To*, and *Net*) for the 20 MSAs. Figure 3 shows that there is a minimal difference in the sum of the influence of the other MSAs on each MSA, and therefore, the *Net* influence of an MSA determines whether this MSA influences other areas. Table 4 and Figure 3 show that the three MSAs in California (i.e., Los Angeles, San Diego, and San Francisco) and Phoenix, Denver, and Miami are MSAs that have a greater influence on the other areas. Table 4 and Figure 3 both show that the coastal U.S. MSAs have a greater influence on other areas and are mainly in California and Florida. Denver is the inland MSA that has the greatest effect. Besides, Table 4 demonstrates that 35.8% of the housing market changes in Denver result from internal factors in the market. This shows that the housing market in Denver is also important.

Table 3 Correlation Coefficients

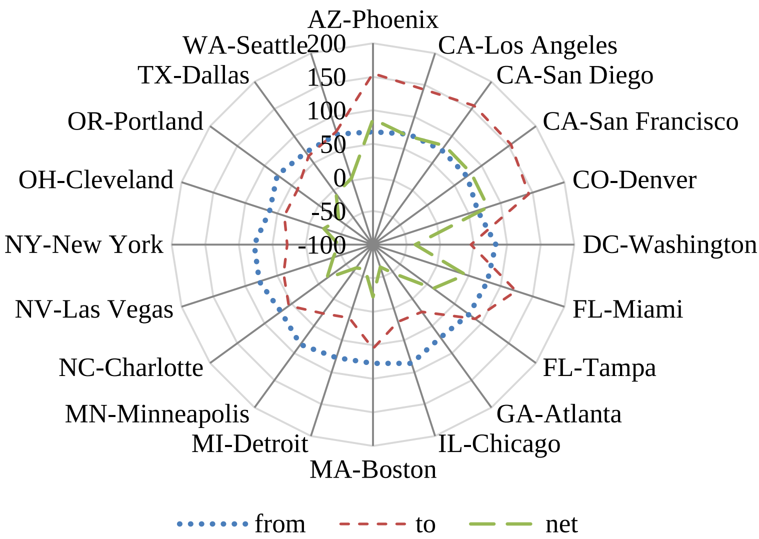
City	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
AZ-Phoenix	1.00	0.81	0.69	0.76	0.52	0.77	0.89	0.85	0.54	0.65	0.47	0.65	0.70	0.51	0.73	0.64	0.41	0.78	0.45	0.78
CA-Los Angeles	0.81	1.00	0.91	0.80	0.49	0.85	0.88	0.82	0.60	0.69	0.59	0.63	0.69	0.45	0.88	0.75	0.41	0.66	0.37	0.68
CA-San Diego	0.69	0.91	1.00	0.83	0.54	0.81	0.80	0.72	0.52	0.64	0.67	0.60	0.70	0.38	0.81	0.71	0.41	0.54	0.38	0.56
CA-San Francisco	0.76	0.80	0.83	1.00	0.67	0.74	0.76	0.72	0.59	0.65	0.64	0.63	0.71	0.45	0.68	0.62	0.44	0.62	0.49	0.64
CO-Denver	0.52	0.49	0.54	0.67	1.00	0.44	0.50	0.55	0.53	0.53	0.58	0.58	0.60	0.41	0.47	0.41	0.47	0.47	0.65	0.56
DC-Washington	0.77	0.85	0.81	0.74	0.44	1.00	0.84	0.78	0.47	0.70	0.66	0.58	0.68	0.34	0.73	0.80	0.44	0.58	0.36	0.56
FL-Miami	0.89	0.88	0.80	0.76	0.50	0.84	1.00	0.89	0.54	0.72	0.58	0.64	0.72	0.48	0.80	0.77	0.40	0.72	0.40	0.75
FL-Tampa	0.85	0.82	0.72	0.72	0.55	0.78	0.89	1.00	0.57	0.73	0.57	0.61	0.66	0.49	0.77	0.74	0.41	0.77	0.46	0.76
GA-Atlanta	0.54	0.60	0.52	0.59	0.53	0.47	0.54	0.57	1.00	0.68	0.47	0.59	0.58	0.50	0.57	0.50	0.37	0.59	0.50	0.62
IL-Chicago	0.65	0.69	0.64	0.65	0.53	0.70	0.72	0.73	0.68	1.00	0.66	0.72	0.71	0.49	0.65	0.74	0.46	0.69	0.48	0.69
MA-Boston	0.47	0.59	0.67	0.64	0.58	0.66	0.58	0.57	0.47	0.66	1.00	0.58	0.67	0.30	0.52	0.66	0.45	0.41	0.43	0.42
MI-Detroit	0.65	0.63	0.60	0.63	0.58	0.58	0.64	0.61	0.59	0.72	0.58	1.00	0.72	0.47	0.64	0.52	0.40	0.57	0.49	0.60
MN-Minneapolis	0.70	0.69	0.70	0.71	0.60	0.68	0.72	0.66	0.58	0.71	0.67	0.72	1.00	0.50	0.61	0.65	0.43	0.60	0.52	0.61
NC-Charlotte	0.51	0.45	0.38	0.45	0.41	0.34	0.48	0.49	0.50	0.49	0.30	0.47	0.50	1.00	0.48	0.39	0.27	0.62	0.45	0.65
NV-Las Vegas	0.73	0.88	0.81	0.68	0.47	0.73	0.80	0.77	0.57	0.65	0.52	0.64	0.61	0.48	1.00	0.67	0.38	0.66	0.36	0.72
NY-New York	0.64	0.75	0.71	0.62	0.41	0.80	0.77	0.74	0.50	0.74	0.66	0.52	0.65	0.39	0.67	1.00	0.40	0.58	0.28	0.60
OH-Cleveland	0.41	0.41	0.41	0.44	0.47	0.44	0.40	0.41	0.37	0.46	0.45	0.40	0.43	0.27	0.38	0.40	1.00	0.40	0.47	0.35
OR-Portland	0.78	0.66	0.54	0.62	0.47	0.58	0.72	0.77	0.59	0.69	0.41	0.57	0.60	0.62	0.66	0.58	0.40	1.00	0.53	0.84
TX-Dallas	0.45	0.37	0.38	0.49	0.65	0.36	0.40	0.46	0.50	0.48	0.43	0.49	0.52	0.45	0.36	0.28	0.47	0.53	1.00	0.51
WA-Seattle	0.78	0.68	0.56	0.64	0.56	0.56	0.75	0.76	0.62	0.69	0.42	0.60	0.61	0.65	0.72	0.60	0.35	0.84	0.51	1.00

Table 4 Full-Sample Connectedness Table

City	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	From
AZ-Phoenix	31.7	4	8	9.3	9	3.8	14.9	3	2.8	0.1	0.4	0.5	0.4	0.5	1	2.3	0.8	1	2.9	3.8	*68*
CA-Los Angeles	11.3	27.2	14.8	8.4	5.7	1.8	8.1	4.8	0.5	0.2	3.8	0.1	0.2	1.5	5.3	0.6	2.3	0.7	1.5	1.5	*73*
CA-San Diego	5.9	22.2	25.6	10.8	7.6	0.9	5.5	3.2	0.1	0.2	5.5	0.1	0.7	2.4	3.7	0.3	2.5	0.4	0.8	1.6	*74*
CA-San Francisco	9.1	10.5	14	26.8	9.2	1.8	6.7	2.5	0.4	0.6	1.4	0.2	0.3	2.6	1.9	2.9	2.7	1.1	2.3	2.9	*73*
CO-Denver	4.5	1	9.8	15.7	35.8	2.2	4.2	4.1	0.2	0.5	3.7	0.6	0.6	4.1	0.5	0.5	1	0.5	6.2	4.5	*64*
DC-Washington	8.3	16.5	11.2	9.4	5	17.2	8.6	4.6	1	0.7	4.1	0.6	0.7	0.8	1.5	2.1	2.6	2.3	1.1	1.8	*83*
FL-Miami	16.4	12.2	8.5	7.8	7.6	2.9	21.3	7.7	1.2	0.3	2.8	0.4	1.8	0.1	2.5	0.5	0.8	0.9	2.1	2.1	*79*
FL-Tampa	13.5	7.4	5.8	7.2	9.1	2.4	11.6	23	1.7	1	3.1	0.3	0.3	0.5	2.3	0.9	1.8	2.1	3.3	2.7	*77*
GA-Atlanta	5	4.4	6.1	7.7	6.7	0.2	2.6	3.8	29.2	1.7	2.3	2.6	0.4	5.4	3.4	1.3	2.5	1.8	7.5	5.2	*71*
IL-Chicago	5.2	6.2	5.7	7.8	5.5	5.2	5.7	7.8	4.2	13.6	2.7	4.2	3	5.7	1.4	2.3	1.9	2.8	4	5.1	*86*
MA-Boston	1.7	6.5	11	11.4	12.1	2.4	3.1	3.7	0.4	2	23.1	0.9	2.3	4.5	0.7	4.8	4.4	1.2	1.2	2.8	*77*
MI-Detroit	7.4	3.2	9	8.4	11.2	1.1	4.3	1.4	1.9	7	2.2	23.3	5.8	5	2.2	1.2	0.1	0.6	2.3	2.3	*77*
MN-Minneapolis	8.1	4.1	9	9.9	11.9	2.6	7.4	4.8	0.8	1.9	2.5	2.1	16.3	3.3	0.9	1.7	2.4	1.9	3.8	4.7	*84*
NC-Charlotte	7.5	2.4	3.3	5.5	2.7	0.8	4.6	3.1	2.6	0.9	4.3	0.1	3.3	29.7	2.9	2.4	1.1	7.3	3.8	11.6	*70*
NV-Las Vegas	8.3	22.3	17.2	3.6	5	0.2	4.8	1.8	0.2	0.1	2.3	0.7	0.9	4.4	22	0.3	0.3	0.3	0.6	4.4	*78*
NY-New York	3.9	11.3	6.6	6.5	4.1	6.3	6	10.2	1	1.3	6.8	0.6	1.2	2.6	0.7	22.5	5.2	0.5	0.8	1.8	*77*
OH-Cleveland	4.4	3.3	5.3	4.1	8	3.9	4	4.5	1.3	1	3.6	0.5	2	3.3	1.1	1.3	38	1.2	5.4	3.6	*62*
OR-Portland	13.8	2.1	1.7	5.9	5.5	3.1	8.7	7.3	1.2	0.5	0.6	0.6	0.3	1.8	3	0.9	2.5	23.9	8.3	8.2	*76*
TX-Dallas	5.8	0.4	4.5	7.6	11.4	3.2	5.1	3.6	1.5	0.7	2.9	0.2	1.7	3.4	0.9	1	3.4	6.4	29.8	6.4	*70*
WA-Seattle	15	2.9	4.2	7.4	6.1	1.2	8.3	5.7	1.2	0.2	0.3	0.2	0.8	3	4.4	0.9	0.2	5.5	5.3	27.2	*73*
To	*155*	*143*	*156*	*154*	*144*	*46*	*124*	*88*	*24*	*21*	*55*	*15*	*27*	*55*	*40*	*28*	*39*	*39*	*63*	*77*	**74.60%**

Note: Numbers in italics represent the directional contribution from/to other markets. The percentage in the lower right end corner in bold is the total connectedness

Figure 3 Connectedness of Full Sample

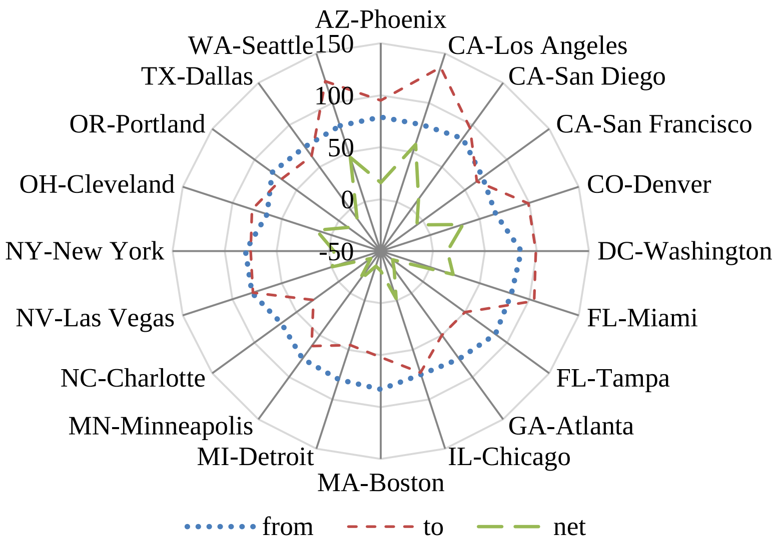


The results in Table 4 are based on all-sample estimates. We continue to estimate the connectedness before (1991–2006), during (2005–2010), and after (2007–2018) the subprime mortgage crisis. To facilitate comparison, Figs. 4–6 show the total directional connectedness measures (*From*, *To*, and *Net*) before, during, and after the subprime mortgage crisis. Figure 4 shows that the 20 MSAs have approximately the same amount of influence on each other before the subprime mortgage crisis. No situations are found in which the effect of the coastal cities on inland areas or the west coast on the east coast is greater. Figure 5 shows that only a few MSAs have a positive net impact (C_i^H>0) during the subprime mortgage crisis. Figure 6 shows that after the subprime mortgage crisis, the more influential MSAs are clustered along the coast and mostly in California and Florida except for Denver.

Figure 7 shows the geographical locations of MSAs with a positive net impact (C_i^H>0) in different periods of time. Few MSAs have a positive net impact during the subprime mortgage crisis and those that have a positive net impact are mostly found along the coast. West coast cities are more influential after the subprime mortgage crisis than they were before the crisis.

Figures 3–7 illustrate the spatial changes in the effects of housing markets in major U.S. cities. Subsequently, we use rolling windows for estimation, obtaining dynamic total connectedness measures to observe changes in connectedness over time[4]. We estimate total connectedness over 60-month rolling-sample windows. Figure 8 shows the changes in the connectedness of 20 cities over time and indicates that the increase in total connectedness took place gradually before October 2007, which means that the systematic risks of these markets consistently increased until October 2007 after which they are reduced. However, the market connectedness considerably increased in November 2008 until July 2009 when systematic risks decline again due to the bankruptcy of the Lehman Brothers. From 2014 to the beginning of 2018, the connectedness of housing markets in metropolitan areas, that is the systematic risks linked to these markets, did not increase and was less than the connectedness prior to the subprime mortgage crisis even though these housing markets return to their level of connectedness before the subprime mortgage crisis. This trends shows that this wave of increasing house prices (2014–2018) is comparatively more enduring than the high house prices in 2006.

Figure 4 Connectedness before Subprime Mortgage Crisis



[4]The number of periods for the rolling windows is based on the shortest period for estimating a complete set of total connectedness indices. This paper begins estimation by using 60-month rolling windows because the VAR model for the two lag periods of the 20 variables is estimated. Diebold and Yilmaz (2014) note that as the window length is reduced, the variations in the dynamic connectedness increase. Therefore, using a large window length can provide relatively accurate estimates of connectedness between markets. Antonakakis et al. (2018) use data from Q41973–Q42014 to measure the connectedness of 13 regions in the United Kingdom. They also use 60-quarter rolling windows to determine the correlation between major events and market connectedness.

Figure 5 Connectedness during Subprime Mortgage Crisis

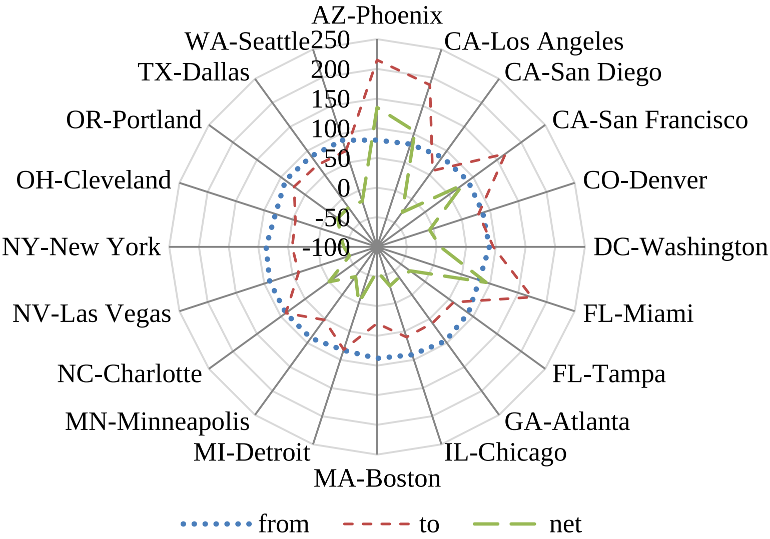


Figure 6 Connectedness after Subprime Mortgage Crisis

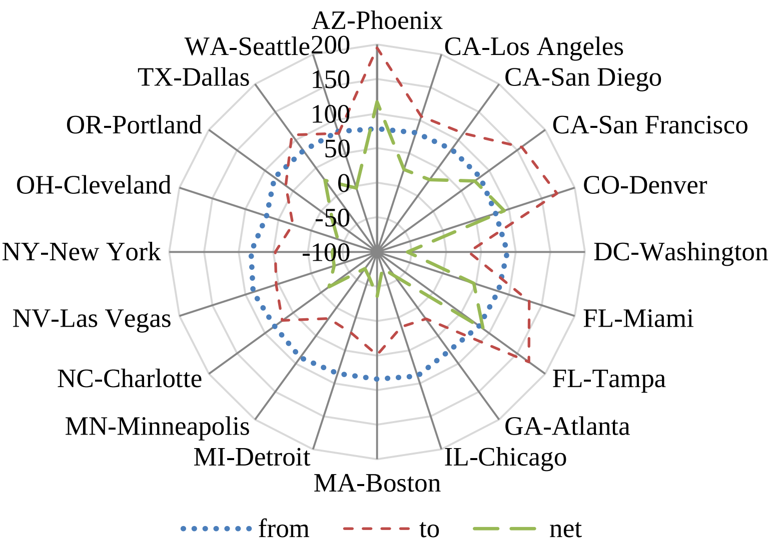


Figure 7 **Positive Net Influences**

Panel A **Full Sample**

Panel B **Before Subprime Mortgage Crisis**

Panel C **Subprime Mortgage Crisis**

Panel D After Subprime Mortgage Crisis

4.2 Connectedness of Housing Markets and Other Markets

Figure 8 shows that the systematic risks linked to these markets are attributable to the subprime mortgage crisis and the bankruptcy of the Lehman Brothers, thus suggesting that the connectedness of housing markets in these metropolitan areas probably contains warning signals for market risks.

Figure 8 Variations in Connectedness

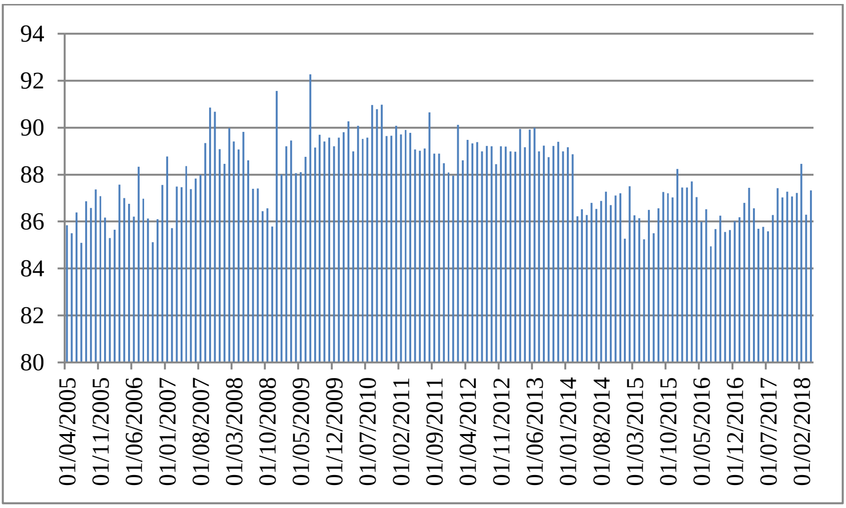


Figure 8 indicates that the connectedness of the regional housing markets continuously increased before October 2007, which shows that the systematic risk of the housing market in the U.S. was increasing at the time. Systematic risk peaked during the subprime mortgage crisis in 2007 before substantially declining. Systematic risk continued to fall until October 2008 and then began to increase until August 2010, peaking again at this point in time. The period from October 2008 to August 2010 is between two financial crises, namely the bankruptcy of the Lehman Brothers which resulted in a global economic recession and the European sovereign debt crisis during which contravention of relevant statutes could occur. The financial crisis in 2007 was due to the housing market; therefore, the systematic risk between regional housing markets can be a useful variable for early warning of housing market recession. Such a systematic risk, which showed an increasing trend between October 2008 and August 2010, may be used for evaluating the overall market risk during the said period possibly because the economic performance of the market considerably declined during this period of time, thus prompting the US Federal Reserve System to stimulate the market through quantitative easing. This monetary policy might have given the market a sufficient amount of capital, thus resulting in an increase in the systematic risk.

Next, we analyze whether the dynamics of the connectedness inside housing markets are related to the connectedness of housing markets and other markets. In other words, we discuss whether the systematic risks of regional housing markets are attributable to the ability of housing markets to disseminate information. Therefore, we estimate the connectedness among housing, stock, bond, and foreign currency markets across the U.S. The related data are taken from the S&P/Case–Shiller HPI Composite 20, S&P 500 Index, U.S. 10-year bond yield, and USD index, respectively. The simple statistics of these four market datasets are presented in Table 5, which shows that the stock markets fluctuate the most. Using the index return data of these four markets, we estimate the full-sample connectedness, as shown in Table 6.

Table 5 Descriptive Statistics for Data from Four Markets

Market	Housing market (index)	Stock market (index)	Bond market (%)	Foreign exchange market (index)
Mean	161.14	1460.92	3.52	90.08
Median	159.48	1321.67	3.59	87.06
Maximum	210.77	2823.81	6.66	120.28
Minimum	100.59	735.09	1.46	71.80
Std. Dev.	29.31	462.42	1.25	12.14
Skewness	-0.07	0.97	0.23	0.79
Kurtosis	1.98	3.13	2.11	2.74

Note: This table shows the connectedness among housing, stock, bond, and foreign currency markets across the U.S. The data that we use are taken from the S&P/Case–Shiller HPI Composite 20, S&P 500 index, U.S. 10-year bond yield, and USD index, respectively.

Table 6 presents the total directional connectedness measures of the estimated data and shows that the housing markets have the lowest net impact on the other markets, and the sum of the effects of the housing markets on the other three markets is 3, whereas the sum of the effects of the other markets on the housing markets is 16. Hence, the net impact of the housing markets is –13. Among the stock, bond, and foreign currency markets, the stock market has the greatest impact on the housing markets. Table 6 shows the static, unconditional connectedness among these markets. Subsequently, we use 24-month rolling-sample windows to obtain the changes in dynamic connectedness, as illustrated in Figure 9. Figure 9 shows that the highest risks linked to these markets are found in July 2009 and consistent with the highest systematic risks in the regional housing markets. The housing markets have the lowest net impact, but whether the ability of housing markets to disseminate information increases when systematic risks in regional housing markets increase must be determined. Figure 10 illustrates the net impact of the S&P/Case–Shiller HPI Composite 20 returns on the stock, bond, and foreign currency markets. The figure shows that from 2007 to April 2010, the housing markets have a positive net impact on the stock market with the exception of April to August 2008. As for the effect of the bond and foreign currency markets, the net impact of the housing markets peaks in May 2006, which is the period when the systematic risks of regional housing markets are increasing. Antonakakis et al. (2016) and Damianov and Elsayed (2018) verify that housing markets tend to influence the overall economy and other markets during an economic depression, which is consistent with the results presented in our paper.

Table 6 Connectedness between Markets

Connectedness	Housing market	Stock market	Bond market	Foreign exchange market	Other
Housing market	84.5	9.1	5.1	1.3	*16*
Stock market	0.9	84.3	4.2	10.7	*16*
Bond market	2.3	10.8	84.9	2.0	*15*
Foreign exchange market	0.3	11.5	1.8	86.4	*14*
Contribution to others	*3*	*31*	*11*	*14*	60
Contribution including own	88	116	96	100	**15.0%**

Note: Numbers in italics represent directional contribution from/to other markets. The percentage in the lower right end corner in bold is the total connectedness

Figure 9 Connectedness among Four Different Markets

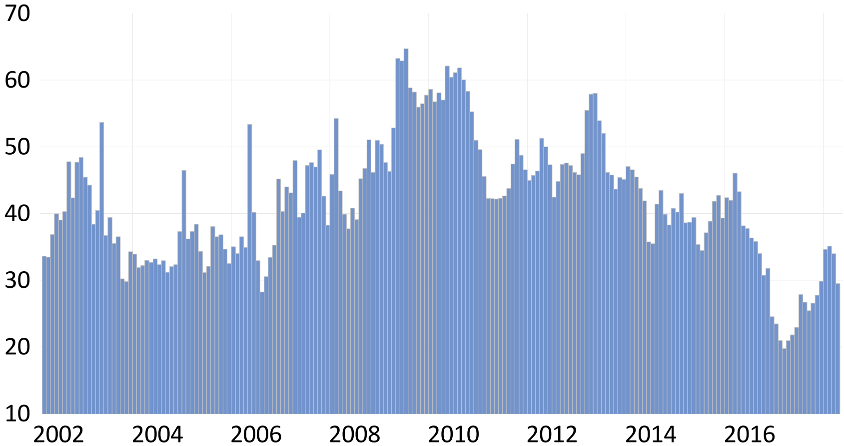
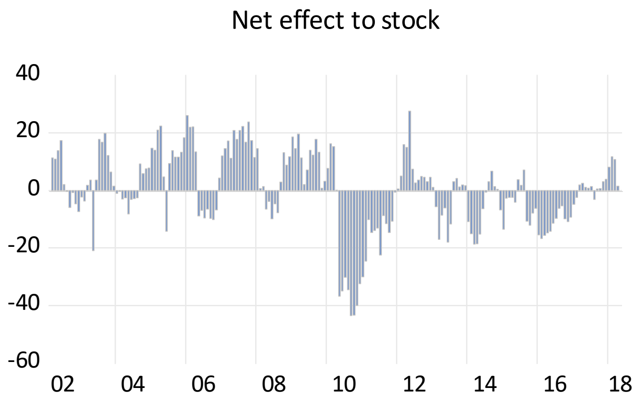
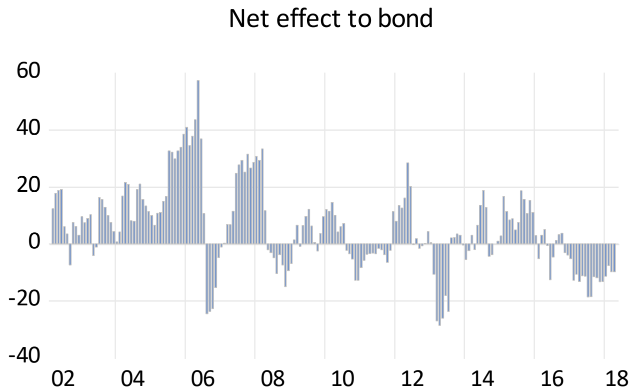
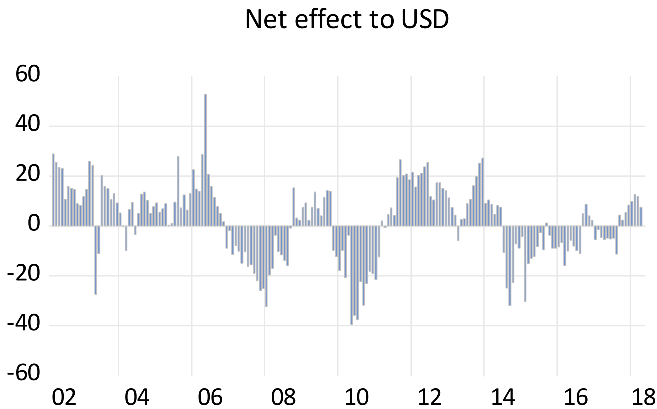


Figure 10 Net Effects of Housing Market







4.3 Effects of Regional Housing Connectedness on Overall Economy

Aastveit et al. (2017) state that the possibility of market bubbles means that the Federal Reserve examines the house price growth rate when considering monetary policies. This paper thus examines the increase in connectedness of the housing markets in metropolitan areas next; that is, whether monetary policies respond to increasing systematic risks of the regional housing markets and the effects of this response on the risk of default in the U.S. housing markets. The findings provide insight into whether the effects of housing markets on the entire economy and other markets emerge from the increase in monetary control and risks of default caused by systematic risks.

The total connectedness among the housing markets in the 20 MSAs estimated based on Figure 8 is used as the measure of housing linkage, that is, the systematic risk of the regional housing markets. Seasonally adjusted M1 is used as the proxy for changes in short-term monetary policies[5]. Table 7 presents the causal relationship between the money supply and the total connectedness of

[5] Unit: US$ 1 billion.

the housing market. The total connectedness significantly affects the rate of growth of the money supply, but this rate of growth did not significantly influence the total connectedness of the housing market during this period of time.

Table 7 Granger Causality Tests

Null Hypothesis	F-Statistic	p-value
Mg does not Granger Cause $Cong$	0.4761	0.6222
$Cong$ does not Granger Cause Mg	**4.6872**	0.0107

Note: The data of connectedness and money supply is represented by $Cong$ and Mg, respectively. The number in bold denotes significance at the 5% level.

Many previous studies have concluded that central banks may respond to asset price fluctuations (Gilchrist and Leahy, 2002; Ida, 2011). The higher connectedness among the housing markets implies more systematic risk of the regional housing markets. Monetary policies may also respond to increases in systematic risks. In addition, the data period of this study includes the housing bubble and the subprime mortgage crisis which might have compelled the Federal Reserve to substantially modify its monetary policy. Hence, as we can see in Table 7, total connectedness can affect the rate of growth of the money supply, which is consistent with the findings in previous studies.

Then we use a VAR model and impulse response function to analyze and demonstrate the relationship between the money supply and the systematic risk of the housing market. Additionally, this paper uses the subprime mortgage market default index as a measure of default risk[6] because the recent housing crisis in the U.S. was caused by subprime mortgages. Figure 11 provides a time-series diagram of monetary supply and default risk. Default risk is the highest from February 2008 to July 2009 during the data period. The M1 growth rate is highest in December 2008, which is when the Federal Reserve began to considerably increase the monetary supply in response to the bankruptcy of the Lehman Brothers so as to halt the stock market decline and economic downturn.

Table 8 presents the estimated relationships among total connectedness, monetary supply, and subprime mortgage default index. The rate of growth of these three variables is used to ensure that the data are all stationary. The table shows that among the three variables, total connectedness is the most exogenous variable that is affected by its lag. Monetary supply is affected by total connectedness; if the systematic risks of housing markets increase, monetary supply is reduced after two periods, possibly because the Federal Reserve intervenes in fear of housing market overheating. In the next period, a contractionary monetary policy is applied, which leads to an increase in the risk

[6] The data used in this paper is obtained from the S&P Dow Jones Indices database. This index measures the default rates across second mortgages.

of subprime mortgage default. To present this series of effects more clearly, Figure 12 is an impact response analysis of the significant variables in Table 8; that is, the impact of total connectedness on the monetary policy and the impact of monetary policy on default risk. Figure 12 shows that after total connectedness is increased by a standard deviation, the rate of growth in the monetary supply is reduced by 0.16%; this impact is nil after 6 months. After the rate of growth of the monetary supply is increased by a standard deviation, the default rate decreases by 1.9%; therefore, a decline in monetary supply growth rate (contractionary monetary policy) causes an increase in the default rate. Table 8 and Figure 12 imply the existence of a means in which an increase in the linkage of regional housing markets negatively influences the overall economy.

Table 8 Connectedness, Money Supply and Default Risk

Vector Autoregression Estimate			
Variable	$Cong$	Mg	DRg
	-0.5187	-0.1451	-0.1707
$Cong_{t-1}$	(0.0841)	(0.0734)	(0.7192)
	[-6.1694]	[-1.9775]	[-0.2373]
	-0.1522	**-0.2006**	-0.0847
$Cong_{t-2}$	(0.0849)	**(0.0741)**	(0.7263)
	[-1.7927]	**[-2.7086]**	[-0.1167]
	0.0863	0.0239	**-2.0973**
Mg_{t-1}	(0.1007)	(0.0878)	**(0.8610)**
	[0.8573]	[0.2717]	**[-2.4359]**
	-0.0384	0.1784	-0.4828
Mg_{t-2}	(0.1049)	(0.0915)	(0.8972)
	[-0.3662]	[1.9498]	[-0.5381]
	0.0132	-0.0039	0.3322
DRg_{t-1}	(0.0098)	(0.0086)	(0.0840)
	[1.3453]	[-0.4508]	[3.9543]
	0.0110	-0.0073	-0.0169
DRg_{t-2}	(0.0099)	(0.0087)	(0.0850)
	[1.1065]	[-0.8409]	[-0.1988]
	0.0001	0.0052	0.0141
$Constant$	(0.0013)	(0.0011)	(0.0111)
	[0.0483]	[4.5809]	[1.2708]
R-squared	0.2253	0.0835	0.1468
Adj. R-squared	0.1927	0.0450	0.1110
Log likelihood	459.4309	479.8882	137.4575
Akaike AIC	-6.0324	-6.3052	-1.7394
Schwarz SC	-5.8919	-6.1647	-1.5989
Log likelihood		1080.0590	
Akaike information criterion		-14.1208	
Schwarz criterion		-13.6993	

Note: The data of the connectedness, money supply and default risk are represented by $Cong$, Mg and DRg, respectively. Entry in parenthesis stands for standard deviations and the t-statistics. The number in bold denotes significance at the 5% level.

Figure 11 Money Supply and Default Rate

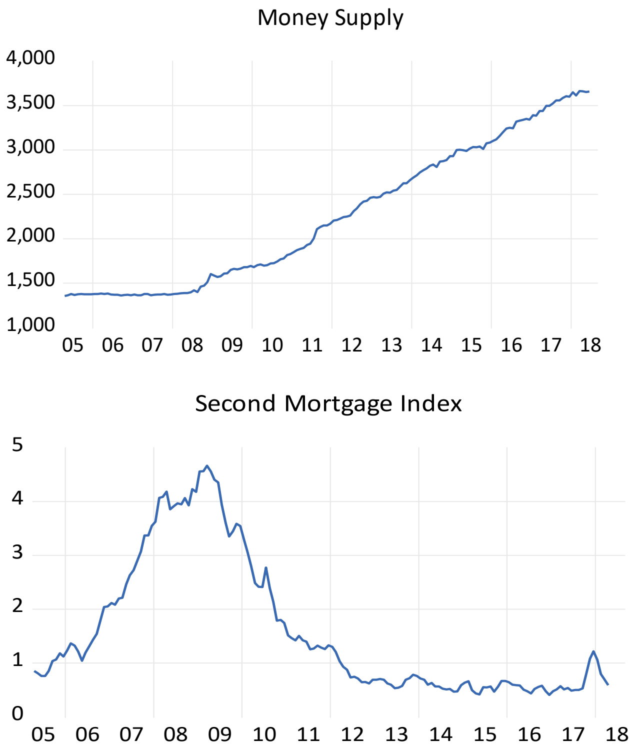
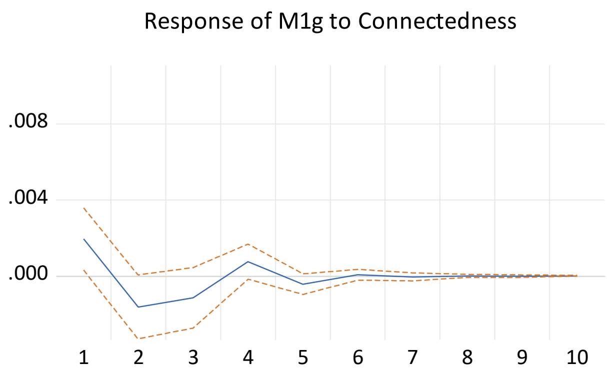
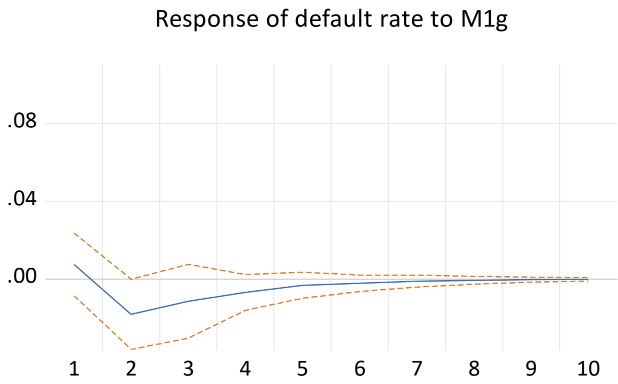


Figure 12 Influence of Connectedness





5. Conclusion

Using the house price indices of 20 MSAs across the U.S. for the period of January 1991 to April 2018, this paper analyzes the changes and effects of connectedness of the housing markets in MSAs in the U.S. First, spatial changes in the effects of housing markets in major U.S. cities show that out of all the samples, the housing markets in west coast MSAs are the most influential, and the spatial distribution of this influence is affected by the subprime mortgage crisis because few MSAs have a positive net impact during the crisis period and are found along the coast. The influence of west coast cities increases after the subprime mortgage crisis compared to that before the crisis, probably because the house prices in these cities recover more quickly.

Second, changes in connectedness over time are found to be affected by the subprime mortgage crisis. Before October 2007, the total connectedness of the housing markets in the 20 MSAs gradually increased, but the Lehman Brothers financial crisis resulted in yet again a considerable increase in connectedness in 2008. Since 2014, the connectedness of housing markets in metropolitan areas of the U.S. is less than before the crisis even though most of the house prices have reverted back to those before the subprime mortgage crisis took place. This paper infers that such house price recovery is constant and the systematic risks are low.

Third, this paper finds that the systematic risks of housing market linkage in U.S. MSAs are related to the subprime mortgage crisis and the Lehman Brothers financial crisis, thus suggesting that the connectedness between these metropolitan housing markets probably contains a warning signal for market risks. We further estimate the connectedness among the housing, stock, bond, and foreign currency markets in the U.S. to discuss whether the systematic risks of regional housing markets are related to the ability of housing markets to disseminate information or spread risks. We find that when housing markets generate positive net impacts on other markets, the systematic risks of regional housing markets gradually increase, thus indicating that an increase in regional housing market linkage leads to an increase in the external impact of the overall housing market.

Finally, the evidence in our study shows that the monetary supply decreases following an increase in systematic risks, probably because the Federal Reserve intervenes in fear of housing market overheating, and the contractionary monetary policy prompts an increase in the risk of subprime mortgage default. The results of this study show the means in which increasing the linkage of regional housing markets negatively influences the overall economy. In addition, our results imply that increasing connectedness affects the connectedness of housing markets with other financial markets as well as the possibility of an economic bubble in the overall economy, which causes monetary policies to contract, thereby increasing default risk. The dissemination of default risk increases the probability of financial risks. Investors and the government are advised to observe the connectedness of regional housing markets to monitor the risks linked to the housing markets and other financial markets, as well as the risks that are produced to the overall economy.

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