

Time-varying connectedness of metropolitan housing markets

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Abstract

We construct a time-varying measure of connectedness for 382 U.S. metropolitan housing markets using monthly house price data from 1975 to the present. Housing connectedness in the long run is found to be much stronger than the instantaneous connectedness, both of which exhibit notable variation over time and across metropolitan areas. Unlike stock market connectedness, housing market connectedness leads the business cycle; it helps predict the likelihood of future recessions.

KEYWORDS

metropolitan housing markets, recession prediction, time-varying connectedness

1 | INTRODUCTION

As evident from the global financial crisis more than a decade ago, housing markets have experienced shocks, some of which on a more global scale, whereas others are more regional in their scope and magnitude. Early research by Tirtiroğlu (1992), Clapp and Tirtiroğlu (1994), Clapp et al. (1995), Gatzlaff and Tirtiroğlu (1995), Cho (1996), and Dolde and Tirtiroğlu (1997), among others, has emphasized the notion of price diffusion or the ripple effect associated with housing market shocks and the transmission of such shocks across both space and time. Meen (1999) was among the first to suggest that the ripple effect through spatial interactions and information spillover that links housing markets will eventually lead to the convergence of house prices in the long run. This long-run convergence hinges in part on the mobility of labor and financial capital with respect to household migration patterns, the conversion of accumulated home equity, spatial arbitrage in relation to expected future house prices, and the spatial correlation of the determinants of house prices across regions.

In this regard, the literature on the ripple effect or price diffusion associated with regional housing markets has accelerated in recent years, especially in the wake of the housing market implications from the global financial crisis in 2007–2008. These studies have primarily focused on several econometric approaches: unit root/cointegration techniques, Phillips-Sul club convergence tests, dynamic spatial panel models, and the vector autoregression (VAR) framework inherent in the Diebold–Yilmaz spillover effects and connectedness indices.

In the context of high-dimensional serially dependent time-series analysis, factor models have become a leading method; see Stock and Watson (2016) for a review of dynamic factor models and factor-augmented VARs. As a general approach, the general dynamic factor model (GDFM) proposed by Forni et al. (2000) aims to identify a few unobserved shocks or factors, loaded via time-invariant filters, which drive covariances across the panel. Barigozzi et al. (2021) extend Forni et al. (2000)'s time-invariant framework and propose the time-varying GDFM (tvGDFM) by allowing the factors to be loaded via time-varying filters. Due to its time-varying and semiparametric feature, this method is particularly useful in the study of time-varying connectedness in financial markets with a large number of cross sections. In light of the econometric approaches undertaken to date, to the best of our knowledge, the present study is the first to adopt the tvGDFM for the study of housing connectedness at the metropolitan statistical area (MSA) level.

We fit the tvGDFM to monthly returns of 382 U.S. metropolitan housing markets between February 1975 and January 2022 in constructing the time-varying instantaneous and long-run connectedness measures between each pair of MSAs. A few interesting findings emerge. First, variation in housing connectedness over time dominates the cross-sectional variation. Second, housing connectedness over the long run is much stronger than the instantaneous connectedness. Third, both instantaneous and long-run connectedness measures exhibit notable variation over time, and both move with major housing downturns. Fourth, unlike stock market connectedness in Barigozzi et al. (2021), housing market connectedness leads the business cycle.

The phase of the business cycle affects the level of activity in real estate markets and the performance of real estate investment trusts; see Ewing and Payne (2005). Motivated by the leading nature of housing connectedness, this study extends to the use of the connectedness measure to predict the onset and end of recessionary episodes. After controlling for the yield spread and national housing return, housing connectedness remains a significant predictor for future recessions. An increase in housing connectedness heightens the likelihood of future recessions. This result is intuitive. Synergistic declines of regional housing markets are more likely to be associated with recessions. Taking into account the connectedness of regional housing markets also improves the out-of-sample predictive accuracy. Housing connectedness therefore has important implications for both residential and commercial real estate investors.

Connectedness is central to modern risk measurement and management; see Diebold and Yilmaz (2014). It captures key aspects of market risk. Accounting for the connectedness of regional housing markets, market participants and policymakers can be better equipped to assess in real time the likelihood of an economic downturn. For reasons related to the Covid-19 pandemic, the U.S. housing markets are experiencing the largest price run-ups over the past four decades. There is growing concern that U.S. house prices cannot be justified by fundamentals and a correction is likely.¹ Given that housing connectedness at the present moment is higher than that during the last housing boom, which preceded the financial crisis of 2007–2008, real estate investors should

¹ See the March 2022 Federal Reserve Bank of Dallas article “Real-Time Market Monitoring Finds Signs of Brewing U.S. Housing Bubble” at <https://www.dallasfed.org/research/economics/2022/0329> <https://www.dallasfed.org/research/economics/2022/0329>.

watch the behavior of house prices together with their connectedness to react quickly and avoid severe consequences of a recession.

The remainder of this study is as follows. Section 2 surveys the literature on the ripple effect of regional house prices. Section 3 introduces the methodology and data. Section 4 presents the housing connectedness measures and investigates their predictive power for future recessions. Section 5 provides concluding remarks.

2 | LITERATURE REVIEW

The literature on the ripple effect and the long-run convergence of regional house prices has its foundation in the studies on house price diffusion from the Greater London and South East regions to other regions within the United Kingdom.² The review of the literature to follow pertains to the ripple effect in the U.S. housing markets across different levels of aggregation.

Pollakowski and Ray (1997) apply autoregressive integrated moving average (ARIMA) and VAR models to examine price diffusion between nine U.S. census divisions and between the five largest primary MSAs within the New York–Northern New Jersey–Long Island consolidated MSA. Their findings indicate that contiguous spatial diffusion is present only at the local or metropolitan level. Clark and Coggin (2009) deploy an unobserved components model to investigate the convergence of regional house prices through pairwise unit root tests with allowance for structural breaks and find mixed results with respect to convergence. Kim and Rous (2012) utilize the Phillips and Sul (2007) convergence approach in the case of U.S. regional and state-level house prices to reveal multiple convergence clubs with housing supply regulation and climate serving as two significant determinants of convergence club membership. Payne (2012) tests the ripple effect of house prices across the nine U.S. census regions using an autoregressive distributed lag modeling framework to provide evidence supportive of the ripple effect and long-run convergence in regional house prices. Nissan and Payne (2013) test for σ -convergence in U.S. house prices across eight Bureau of Economic Analysis regions and 50 U.S. states to discover that house prices in New England, Mideast, and the Far West converge to overall U.S. house prices, whereas the other regions diverge, and at the state level, only 9 of the 50 U.S. states present evidence of convergence to the overall U.S. house price index. In an examination of nine U.S. regional housing markets, Yunus and Swanson (2013) reveal through multivariate cointegration and error correction modeling that regional markets are integrated with the degree of integration across regional markets enhanced in the postglobal financial crisis period. Miles (2015) employs measures of synchronicity and similarity for house prices across nine U.S. regional housing markets to discover the decreasing integration of housing markets reflective of market segmentation until 2005 after which the degree of integration increases. Tsai (2018) investigates the ripple effect across four U.S. regional housing markets using the spillover and connectedness indices of Diebold and Yilmaz (2009) to

² The early literature on the United Kingdom emphasized the role of Greater London and South East regions in driving house price dynamics; see Rosenthal (1986), Giussani and Hadjimatheou (1991), MacDonald and Taylor (1993), Alexander and Barrow (1994), Drake (1995), Ashworth and Parker (1997), Meen (1999), Cook and Holly (2000), Cook and Thomas (2003), Cook (2003, 2005a, 2005b, 2006, 2012), Worthington and Higgs (2003), Holmes (2007), Holmes and Grimes (2008), Holly et al. (2011), Abbott and De Vita (2012, 2013), Gray (2012, 2018, 2021), Montagnoli and Nagayasu (2015), Cook and Watson (2016), Antonakakis et al. (2018), Hudson et al. (2018), Kyriazakou and Panagiotidis (2018), Begiazi and Katsiampa (2019), Holmes et al. (2019), Tsai (2014, 2015, 2020), Miles (2020), Cascio (2021), and Zhang et al. (2021). Please note the literature includes analysis of ripple effects associated with house prices in other countries beyond the United Kingdom and United States. To conserve on space, we focus our attention on the literature pertaining to the United States.

find that the ripple effect is associated with the transaction volume of regional housing markets more than house prices.

With a focus at the U.S. state level, Holly et al. (2010) evaluate the determinants of house prices to find a significant spatial dependence related to contiguity. Kuethe and Pede (2011) estimate a spatial VAR model for 11 states in the western United States to show that locational spillovers influence house price movements and provides for improved forecasting performance for housing markets. Using the pairwise testing approach of Pesaran (2007) and Pesaran et al. (2009), Holmes et al. (2011) provide support for the convergence of house prices at the U.S. state and metropolitan levels, and find the distance between regions influences the responsiveness of prices in moving towards long-run convergence. Through the use of fractional cointegration techniques, Barros et al. (2012) fail to identify a cointegrated relationship between U.S. state-level house prices and the U.S. overall house price index. In a related study, Barros et al. (2014) employ fractional integration techniques to analyze whether the degree of persistence in the ratio of U.S. state house prices relative to overall national house prices is stationary (i.e., convergence) in defining the ripple effect. The results show that house price ratios in most states either fail to converge or converge slowly. Montanés and Olmos (2013) utilize the Phillips and Sul (2007) club convergence approach to identify a change in the evolution in U.S. house prices at the state level in the aftermath of the global financial crisis with evidence of market segmentation. Brady (2014) uses impulse response analysis from a spatial autoregressive model to estimate the spatial diffusion of house prices across the 48 contiguous U.S. states and the District of Columbia. The findings show significant spatial diffusion and persistence for up to 3–4 years following a price increase across regions.

In addition, several studies examine housing convergence at the county level. Gallet (2004) utilizes unit root tests with allowance for structural breaks to examine convergence among house prices at the county level (Orange, Los Angeles, Riverside, San Bernardino, and Ventura) of the Los Angeles region. The results reveal the convergence of house prices within clusters differentiated by coastal and inland counties. Brady (2011) introduces a dynamic spatial model with impulse response function analysis to show that diffusion of regional house prices across California counties may last up to two and half years. In a related replication study of Brady (2011), Shen and Pang (2018) highlight the sensitivity of the results to use of different house price indices.

At the U.S. metropolitan level, Kang (2011) estimates a dynamic panel model in the case of 42 U.S. MSAs to show the high-tech industrial transmission mechanism and not spatial diffusion drives house price convergence. Miao et al. (2011) investigate the transmission of housing returns and volatility across 16 U.S. metropolitan areas to support the interconnectedness of housing markets and with volatility dependency illustrating the information linkages among markets. Canarella et al. (2012) employ a battery of unit root tests with structural breaks to examine the ripple effect with respect to the ratio of metropolitan house prices to the S&P/Case Shiller Composite-10 home price index. Their results provide mixed evidence on the stationarity of the house price ratios. Gupta and Miller (2012a) explore the causal dynamics of house prices between Los Angeles, Las Vegas, and Phoenix to find that Los Angeles house prices Granger-cause Las Vegas and Phoenix house prices, and Las Vegas house prices Granger-cause Phoenix house prices. In another related study, Gupta and Miller (2012b) examine the causal dynamics of house prices across eight Southern California metropolitan areas to identify a long-run relationship between house prices in these metropolitan areas. Zhu et al. (2013) use a dynamic spatial panel model with general autoregressive conditional heteroskedasticity to explore the regional interactions across 19 U.S. metropolitan housing markets. Their results suggest significant spatial interdependence in housing returns based on both geographic proximity and economic similarity. Kallberg et al. (2014) examine 14 U.S. metropolitan housing markets to show that house prices in geographically diverse U.S. metropolitan areas are based on common fundamental fluctuations in mortgage

rates, realized and expected inflation, and gross domestic product (GDP) growth. The observed comovement among the 14 metropolitan housing markets has increased over time with excess covariation (i.e., contagion effects) explaining only a relatively small proportion of the comovement. Damianov and Escobari (2016) utilize cointegration and error correction models to examine the relationship between high and low house price tiers across 364 U.S. metropolitan areas. Damianov and Escobari (2016) find a shift in the long-run equilibrium during the recent housing bubble with the cointegration parameter linking the price tiers greater in absolute value compared to other periods. Moreover, their results also reveal that during the housing bubble lower price tier, homes appreciated and depreciated at higher rates. Chiang and Tsai (2016) undertake forecast error variance decomposition and copula analysis for house prices across eight U.S. metropolitan housing markets to discover that Los Angeles, Miami, and New York are considered as the source for shocks in the western, southern, and eastern regions of the country, respectively. Moreover, Chiang and Tsai (2016) also show that contagion effects in the housing market are prominent in metropolitan areas within the same region than across regional markets. Tsai (2019) uses the Diebold and Yilmaz (2014) spillover index approach to analyze house price spillovers for 10 U.S. metropolitan areas by price tier. Ripples effects are greatest in the lower price tiers with the effects declining during a housing market downturn. Further analysis reveals that money supply growth influences the spillovers.

3 | MODEL AND DATA

A widely adopted method of measuring financial connectedness in the literature is the one proposed by Diebold and Yilmaz (2014). The method relies on generalized forecast error variance decomposition in Pesaran and Shin (1998) of a covariance stationary VAR process. Diebold and Yilmaz (2014)'s measure of connectedness is the ratio of the sum of the off-diagonal elements of the variance decomposition matrix to the sum of all the elements. This method has been applied to regional housing markets in the United Kingdom (see Antonakakis et al., 2018), China (see Zhang and Fan, 2019 and Tsai and Chiang, 2019), and Korea (see Lee and Lee, 2019 and Al-Yahyaee et al., 2021). A time-varying version of Diebold and Yilmaz (2014)'s connectedness measure can be constructed either from a rolling-window VAR estimation (see Chen and Chiang, 2020's application on the China housing markets) or a time-varying parameter VAR (see Andre et al., 2021's application on the U.S. state-level housing markets and Hwang and Suh, 2021 on the Korean markets). Unlike the aforementioned studies, we use the method newly developed by Barigozzi et al. (2021), which outperforms that of Diebold and Yilmaz (2014) in two major aspects. First, the Diebold and Yilmaz (2014) method is fully parametric and cannot handle large cross sections, whereas the Barigozzi et al. (2021) method is based on dynamic principal component analysis jointly with singular VAR estimation and is suitable for studying connectedness of housing markets at a more disaggregated level. Second, the Diebold and Yilmaz (2014) method relies on a covariance stationary model, whereas the Barigozzi et al. (2021) method extends to the local stationary scenario and hence fully accounts for the time-varying feature of connectedness.

3.1 | tvGDFM

The tvGDFM method is based upon a decomposition of a zero-mean double indexed process $\mathbf{X} = \{X_{it} : i \in \mathbb{N}_0, t \in \mathbb{Z}\}$ into a common component χ_{it} and an idiosyncratic component ξ_{it} as follows:

$$X_{it} = \chi_{it} + \xi_{it}, \quad i \in \mathbb{N}_0, t \in \mathbb{Z}, \quad (1)$$

where both components are assumed to follow time-varying moving average processes:

$$\chi_{it} = \sum_{j=1}^q \sum_{k=0}^{\infty} c_{ijk}^*(t) u_{j,t-k}, \quad (2)$$

$$\xi_{it} = \sum_{j=1}^{\infty} \sum_{k=0}^{\infty} d_{ijk}^*(t) \eta_{j,t-k}, \quad (3)$$

and the common component is driven by q factors, $u_1, \dots, u_q$, whereas the idiosyncratic component can be driven by infinitely many shocks. In Equation (1), $\mathbb{N}_0$ denotes the set of natural integers, $\mathbb{Z}$ denotes the set of intergers, and i and t are cross-sectional and time indices.

Such a specification accounts for nonstationarity of these two components and allows their second-order structure to be time-varying. Let n be the number of cross-sectional units, the factor model can be written in the following matrix form:

$$\begin{aligned} \mathbf{X}_{nt} &= \chi_{it} + \xi_{it}, \\ \chi_{nt} &= \mathbf{C}_n^*(t; L) \mathbf{u}_t, \\ \xi_{nt} &= \mathbf{D}_n^*(t; L) \boldsymbol{\eta}_t, \end{aligned} \quad (4)$$

where L is the lag operator, $\mathbf{X}_{nt} = (X_{1t}, \dots, X_{nt})'$, $\chi_{nt} = (\chi_{1t}, \dots, \chi_{nt})'$, $\xi_{nt} = (\xi_{1t}, \dots, \xi_{nt})'$, $\mathbf{u}_t = (u_{1t}, \dots, u_{qt})'$, and $\boldsymbol{\eta}_t = (\eta_{1t}, \eta_{2t}, \dots)'$. The (i, j) th elements of $\mathbf{C}_n^*(t; L)$ and $\mathbf{D}_n^*(t; L)$ are easy to obtain from Equations (2) and (3):

$$c_{ij}^*(t; L) = \sum_{k=0}^{\infty} c_{ijk}^*(t) L^k, \quad 1 \leq i \leq n, 1 \leq j \leq q, \quad (5)$$

$$d_{ij}^*(t; L) = \sum_{k=0}^{\infty} d_{ijk}^*(t) L^k, \quad 1 \leq i \leq n, 1 \leq j < \infty. \quad (6)$$

The (i, j) th element of $\mathbf{C}_n^*(t; L)$ captures the time-varying impulse response function of variable X_{it} to the j th common shock u_j . Let $\hat{\mathbf{C}}_n(t; L)$ denote the estimate of $\mathbf{C}_n^*(t; L)$ and $\hat{c}_{ijk}(t)$ denote the estimate of the (i, j) th element $c_{ijk}^*(t)$, Barigozzi et al. (2021) define their connectedness measurements in analogy to Diebold and Yilmaz (2014), based on the $n \times n$ matrix

$$\hat{\mathbf{Q}}_n(t; L) = \hat{\mathbf{C}}_n(t; L) \hat{\mathbf{C}}_n'(t; L). \quad (7)$$

For example, the instantaneous and long-run connectedness measures are defined as $\hat{\mathbf{Q}}_n(t; 0)$ and $\hat{\mathbf{Q}}_n(t; 1)$, respectively. When $\hat{\mathbf{C}}_n(t; L)$ is evaluated at $L = 0$, it simply equals $\sum_{k=0}^{\infty} \hat{c}_{ijk}(t) 0^k = \hat{c}_{ij0}(t)$, which picks up the estimated impulse response function of variable X_{it} to the j th common shock u_j in the instantaneous period. The quadratic term of $\hat{c}_{ij0}(t)$ therefore measures the forecast error variance of variable X_{it} due to shock j at horizon zero, which makes the measure in Equation (7) analogous to the variance decomposition based connectedness measure of Diebold and Yilmaz (2014). When $\hat{\mathbf{C}}_n(t; L)$ is evaluated at $L = 1$ instead, it equals $\sum_{k=0}^{\infty} \hat{c}_{ijk}(t) 1^k = \sum_{k=0}^{\infty} \hat{c}_{ijk}(t)$, which picks up the estimated impulse response function of variable X_{it} to a permanent shock

u_j . The quadratic term of $\sum_{k=0}^{\infty} \hat{c}_{ijk}(t)$ therefore measures the forecast error variance of variable X_{it} due to shock j at horizon infinity. Moreover, when the matrix $\hat{\mathbf{Q}}_n(t; L)$ is evaluated over a specific frequency band $\Theta \subset [0, \pi]$, one can obtain a spectral connectedness matrix as $\frac{1}{|\Theta|} \sum_{j: \theta_j \in \Theta} \hat{\mathbf{Q}}_n(t; e^{-i\theta_j})$, where $\iota = \sqrt{-1}$; see details in Section 4. To construct these connectedness measures, however, one needs to estimate the impulse response functions $\mathbf{C}_n^*(t; L)$ from the data. The estimate of the impulse response function is easy to obtain in the stationary case but not straightforward when the process $\mathbf{X}$ is not stationary, because in the latter case, one cannot obtain the asymptotic properties of the estimator by letting the number of time periods T tend to infinity. In the presence of nonstationarity, Barigozzi et al. (2021) consider the locally stationary asymptotic scheme of Dahlhaus (1997, 2009). The idea amounts to approximating X_{it} of the nonstationary process $\mathbf{X}_T = \{X_{it} : i \in \mathbb{N}_0, 1 \leq t \leq T\}$ with $X_{it}(\tau)$ of a stationary process $\mathbf{X}(\tau) = \{X_{it}(\tau) : i \in \mathbb{N}_0, t \in \mathbb{Z}\}$ at the rescaled time $\tau = t/T \in (0, 1)$. Here, we briefly outline the method proposed by Barigozzi et al. (2021) following their notation.

For any $\tau \in (0, 1)$, the nonobservable fictitious stationary process of X_{it} , denoted as $X_{it}(\tau)$, can be similarly decomposed into a common component $\chi_{it}(\tau)$ and an idiosyncratic component $\xi_{it}(\tau)$:

$$X_{it}(\tau) = \chi_{it}(\tau) + \xi_{it}(\tau), \quad i \in \mathbb{N}_0, t \in \mathbb{Z}, \quad (8)$$

where

$$\chi_{it}(\tau) = \sum_{j=1}^q \sum_{k=0}^{\infty} c_{ijk}(\tau) u_{j,t-k}, \quad (9)$$

$$\xi_{it}(\tau) = \sum_{j=1}^{\infty} \sum_{k=0}^{\infty} d_{ijk}(\tau) \eta_{j,t-k}, \quad (10)$$

also follow moving average processes driven by the same shocks u_{jt} and η_{jt} as in (2) and (3). Let $\mathbf{X}_{nt}(\tau) = (X_{1t}(\tau), \dots, X_{nt}(\tau))'$, $\chi_{nt}(\tau) = (\chi_{1t}(\tau), \dots, \chi_{nt}(\tau))'$, and $\xi_{nt}(\tau) = (\xi_{1t}(\tau), \dots, \xi_{nt}(\tau))'$, the fictitious stationary process can be written in the following matrix form:

$$\begin{aligned} \mathbf{X}_{nt}(\tau) &= \chi_{nt}(\tau) + \xi_{nt}(\tau), \\ \chi_{nt}(\tau) &= \mathbf{C}_n(\tau; L) \mathbf{u}_t, \\ \xi_{nt}(\tau) &= \mathbf{D}_n(\tau; L) \boldsymbol{\eta}_t. \end{aligned} \quad (11)$$

The difference between the fictitious stationary process in (11) and the nonstationary process in (4) is that $\mathbf{X}_{nt}(\tau)$, $\chi_{nt}(\tau)$, and $\xi_{nt}(\tau)$ are stationary processes and have well-defined spectral matrices, whereas those of $\mathbf{X}_{nt}$, χ_{nt} , and ξ_{nt} do not exist. For any $n \in \mathbb{N}_0$, the $n \times n$ spectral density matrix of $\mathbf{X}_{nt}(\tau)$, by definition, is:

$$\boldsymbol{\Sigma}_n^X(\tau; \theta) = \frac{1}{2\pi} \sum_{\ell=-\infty}^{\infty} e^{-i\ell\theta} \boldsymbol{\Gamma}_n^X(\tau; \ell), \quad \theta \in [-\pi, \pi], \tau \in (0, 1), \quad (12)$$

where $\iota = \sqrt{-1}$ and $\boldsymbol{\Gamma}_n^X(\tau; \ell)$ is the $n \times n$ lag ℓ autocovariance matrix of $\mathbf{X}_{nt}(\tau)$, that is,

$$\boldsymbol{\Gamma}_n^X(\tau; \ell) = E[\mathbf{X}_{nt}(\tau) \mathbf{X}_{n,t-\ell}'(\tau)]. \quad (13)$$

The autocovariance matrix and spectral density matrix of the common component $\chi_{nt}(\tau)$ and the idiosyncratic component $\xi_{nt}(\tau)$ can be defined similarly. Barigozzi et al. (2021) use these spectral matrices as local substitutes for the nonexisting spectral matrices of $\mathbf{X}_{nt}$, χ_{it} , and ξ_{it} .

Based on an $n \times T$ realization of $\mathbf{X}$, denoted as $\mathbf{X}_{nT}$, Barigozzi et al. (2021) propose to estimate the impulse response functions in four steps. The first step estimates the spectral density of $\mathbf{X}_{nt}(\tau)$. For some bandwidth $b_T \in [0, 1/2]$, the local estimator of the lag ℓ autocovariance matrix of $\mathbf{X}_{nt}(\tau)$ is defined based on $M_T = 2Tb_T$ time points between $t - M_T/2 + 1$ and $t + M_T/2$ as follows:

$$\hat{\mathbf{F}}_{n,T}^X(\tau; \ell) = \begin{cases} \frac{1}{M_T} \sum_{s=t-Tb_T+1+\ell}^{t+Mb_T} J\left(\frac{s-t}{M_T}\right) \mathbf{X}_{n,s-\ell} \mathbf{X}_{n,s}' & \text{if } 0 \leq \ell \leq M_T - 1, \\ \hat{\mathbf{F}}_{n,T}^{X'}(\tau; -\ell) & \text{if } -M_T + 1 \leq \ell \leq -1, \end{cases} \quad (14)$$

where $J(\cdot)$ is a kernel function, for example, a uniform kernel as recommended by Zhang and Wu (2021). Note that this autocovariance matrix estimate can be computed only for $t \in [M_T/2, T - M_T/2]$. As a consequence, the connectedness measures of Barigozzi et al. (2021) are not available for any time periods that fall outside of this range. Based on (14), the local estimator of the spectral density of $\mathbf{X}_{nt}(\tau)$ is given by:

$$\hat{\Sigma}_{n,T}^X(\tau; \theta) = \frac{1}{2\pi} \sum_{\ell=-m_T}^{m_T} K\left(\frac{|\ell|}{m_T}\right) \hat{\mathbf{F}}_{n,T}^X(\tau; \ell) e^{-i\ell\theta}, \quad \theta \in [-\pi, \pi], \quad (15)$$

for some $m_T \in \mathbb{N}_0$ that is strictly less than M_T , where $K(\cdot)$ is a kernel function, for example, a triangular kernel as used by Forni et al. (2017). The spectral density in (15) considers m_T frequencies $\theta_j = \pi j / m_T$ with $-m_T \leq j \leq m_T$.

Given the estimated spectral density of $\mathbf{X}_{nt}(\tau)$, the second step, via dynamic principal component analysis, computes the spectral density and autocovariance matrices for the common component $\chi_{it}(\tau)$ as follows:

$$\hat{\Sigma}_{n,T}^X(t/T; \theta_j) = \sum_{j=1}^q \hat{\lambda}_{j;n,T}^X(t/T; \theta_j) \hat{\mathbf{P}}_{j;n,T}^X(t/T; \theta_j) \hat{\mathbf{P}}_{j;n,T}^{X^\dagger}(t/T; \theta_j), \quad (16)$$

$$\hat{\mathbf{F}}_{n,T}^X(t/T; \theta_j) = \frac{2\pi}{m_T} \sum_{j=-m_T}^{m_T} \hat{\Sigma}_{n,T}^X(t/T; \theta_j) e^{i\ell\theta_j}, \quad (17)$$

where $\hat{\lambda}_{j;n,T}^X(t/T; \theta_j)$ is the j th largest, in magnitude, eigenvalue of the estimated spectral density $\hat{\Sigma}_{n,T}^X(t/T; \theta)$ and $\hat{\mathbf{P}}_{j;n,T}^X(t/T; \theta_j)$ is the corresponding eigenvector, which is a complex vector and the $\dagger$ sign in the last term of Equation (16) takes its complex conjugate transpose.

The third step constitutes a stationary static factor model via the following VAR models of dimension $(q + 1)$ for m arbitrary subprocesses of $\chi_{nt}(t/T)$,

$$\mathbf{A}_n^{(k)}(t/T; L) \chi_{nt}^{(k)}(t/T) = \mathbf{H}_n^{(k)}(t/T) \mathbf{u}_t, \quad 1 \leq k \leq m, \quad (18)$$

where $n = m(q + 1)$ and $\mathbf{H}_n^{(k)}(t/T)$ is a $(q + 1) \times q$ matrix of rank q . The orders of the VAR models can be determined by the Akaike information criterion and the Yule-Walker estimates of

$\mathbf{A}_n^{(k)}(t/T; L)$, denoted as $\hat{\mathbf{A}}_{n,T}^{(k)}(t/T; L)$, can be computed from the estimated autocovariance matrix in (17) as for traditional VAR models.³ Let $\hat{\mathbf{A}}_{n,T}(t/T; L)$ be the block diagonal matrix of $\hat{\mathbf{A}}_n^{(k)}(t/T; L)$ with $k = 1, \dots, m$, the following filtered process

$$\hat{\mathbf{Z}}_{nt}(t/T) = \hat{\mathbf{A}}_{n,T}(t/T; L)\mathbf{X}_{nt}, \quad (19)$$

is the estimate of $\mathbf{Z}_{nt}(\tau)$ that forms a stationary static factor model,

$$\mathbf{Z}_{nt}(\tau) = \mathbf{R}_n(\tau)\mathbf{u}_t + \mathbf{A}_n(\tau; L)\xi_{nt}(\tau), \quad (20)$$

for $\tau = t/T$, with the same q common shocks $\mathbf{u}_t = (u_{1t}, \dots, u_{qt})'$.

The fourth and last step estimates the impulse response functions $\mathbf{C}_n^*(t; L)$ through principal component analysis. Similar to (14), the covariance matrix of $\hat{\mathbf{Z}}_{nt}(t/T)$ can be estimated as:

$$\hat{\mathbf{F}}_{n,T}^{\hat{\mathbf{Z}}}(t/T) = \frac{1}{M_T} \sum_{s=t-M_T/2+1}^{t+M_T/2} J\left(\frac{s-t}{M_T}\right) \hat{\mathbf{Z}}_{ns}(t/T) \hat{\mathbf{Z}}_{ns}'(t/T), \quad (21)$$

for $M_T/2 \leq t \leq T - M_T/2$. Let $\hat{\mu}_{j;n,T}^{\hat{\mathbf{Z}}}(t/T)$ denote the j th largest, in magnitude, eigenvalue of $\hat{\mathbf{F}}_{n,T}^{\hat{\mathbf{Z}}}(t/T)$ and $\hat{\mathbf{P}}_{j;n,T}^{\hat{\mathbf{Z}}}(t/T)$ the corresponding eigenvector, the estimate of $\mathbf{R}_n(\tau)$ in (20) can be computed as $\hat{\mathbf{R}}_{n,T}(t/T) = (\hat{\mathbf{R}}_{1;n,T}(t/T), \dots, \hat{\mathbf{R}}_{q;n,T}(t/T))$, where

$$\hat{\mathbf{R}}_{j;n,T}(t/T) = \hat{\mathbf{P}}_{j;n,T}^{\hat{\mathbf{Z}}}(t/T) \sqrt{\hat{\mu}_{j;n,T}^{\hat{\mathbf{Z}}}(t/T)}. \quad (22)$$

Therefore, from Equations (19) and (20), the estimated impulse response function of $\mathbf{X}_{nt}$ to shocks $\mathbf{u}_t$ is:

$$\hat{\mathbf{C}}_{n,T}(t; L) = [\hat{\mathbf{A}}_{n,T}(t/T; L)]^{-1} \hat{\mathbf{R}}_{n,T}(t/T). \quad (23)$$

As mentioned earlier in the paragraph under Equation (7), various connectedness measures can be defined by evaluating the quadratic term of this matrix at different frequencies.⁴

3.2 | Data

We utilize the seasonally-adjusted Freddie Mac House Price Index (FMHPI) data across 382 U.S. MSAs from 1975M1 to 2022M1. The construction of FMHPI is based upon a repeat transactions methodology, a common practice in housing and real estate research, which measures price appreciation by comparing the price of the same property over two or more transactions. The index has

³ The Yule–Walker equation, named for Yule (1927) and Walker (1931), connects the transition matrix with the covariance matrix and the lag autocovariance matrix of the process.

⁴ The above approximation and estimation rely on certain regularity conditions, as detailed in assumptions (A)–(E) on pages 326–330 of Barigozzi et al. (2021). Under these assumptions, Barigozzi et al. (2021) prove the consistency of the estimated time-varying impulse response functions.

TABLE 1 Summary statistics of monthly housing returns

	Mean	SD	Min	Max
Overall	0.359	0.744	−11.004	10.714
Between		0.077	0.173	0.598
Within		0.740	−11.203	10.515

Note: Housing returns are defined as the log difference of house price index and expressed in percent.

extensively been used in housing, real estate, and urban research; see, for example, Akkoyun et al. (2013), Karamon et al. (2017), Christiansen et al. (2019), and Liu et al. (2021) among many others. Compared to other commonly referenced house price indices, for example, the Federal Housing Finance Agency and S&P/Case-Shiller indices, the Freddie Mac House Price Index includes appraisal values used for refinance transactions in addition to purchase transactions. It also differs from other indices in terms of the choice of geographic weights, the method for identifying outliers, and the use of statistical smoothing. For the purpose of our study, the Freddie Mac House Price Index also outperforms other indices for its availability and coverage. For example, while the Federal Housing Finance Agency house price indices at the monthly frequency are available for the United States as a whole and census divisions, MSA-level indices are only available at the quarterly frequency. The S&P/Case-Shiller indices are only available for 20 metropolitan regions. Despite these differences, house price indices from various sources are highly correlated; their pairwise correlation coefficients are higher than 0.99; see Forster and Sun (2022).

We compute housing returns as the log difference of house price index, that is, $HR_{it} = \ln(P_{it}) - \ln(P_{it-1})$, where P_{it} denotes the seasonally adjusted house price index for the i th MSA during month t . Table 1 presents standard descriptive statistics for monthly housing returns at the MSA level ranging from 1975M2 to 2022M1. Monthly housing returns vary between −11% and 10.7%, with an average of 0.36%. Variation over time (i.e., the within variation) dominates the cross-sectional variation (i.e., the between variation).

4 | EMPIRICAL RESULTS

4.1 | Housing connectedness

Let X_{it} in Equation (1) be housing returns HR_{it} . By setting the bandwidths $M_T = 48$ months and $m_T = 24$ months, we fit the tvGDFM on the data set and estimate the spectral density matrix.⁵ The criterion of Hallin and Liška (2007) suggests that the number of factors q equals 2. For $z \in \mathbb{C}$, where $\mathbb{C}$ is the set of complex numbers, with $|z| \leq 1$, we then compute the following estimated matrices:

$$\hat{\mathbf{Q}}_{n,T}(t; z) = \hat{\mathbf{C}}_{n,T}(t; z) \hat{\mathbf{C}}'_{n,T}(t; z), \quad M_T/2 \leq t \leq T - M_T/2, \quad (24)$$

based on which Barigozzi et al. (2021) define their measures of connectedness:

⁵ M_T is the bandwidth used in the estimation of the autocovariance matrix and $m_T < M_T$ is the bandwidth used in the estimation of the spectral density matrix; see Equations (14) and (15). We also use other reasonable values of M_T and m_T , and our results remain robust.

- instantaneous connectedness: $\hat{\mathbf{Q}}_{n,T}(t; 0)$,
- long-run connectedness: $\hat{\mathbf{Q}}_{n,T}(t; 1)$,
- spectral connectedness: $\hat{\mathbf{Q}}_{n,T}(t; \Theta) = \frac{1}{|\Theta|} \sum_{j: \theta_j \in \Theta} \hat{\mathbf{Q}}_{n,T}(t; e^{-i\theta_j})$ within a specific frequency band Θ .

These connectedness measures defined based on variance decomposition as in Equation (24) are appealing for several reasons. First, as Diebold and Yilmaz (2014) illustrate, they are closely related to modern network theory and systemic risk measurement.⁶ Second, they are intuitive and easy to understand, because variance decomposition simply quantifies how much of an entity's future risk is due to a certain shock. Third, connectedness can be easily evaluated at different horizons or frequency intervals to convey different information about market risk.

Figure 1 presents the heatmap of the instantaneous connectedness matrix $\hat{\mathbf{Q}}_{n,T}(t; 0)$ at selected dates during the first decade of the 2000s. The instantaneous connectedness of MSA-level housing returns is relatively smooth over time. In particular, it stays nearly zero both before 2005 and after 2008, and slightly higher during the financial crisis period of 2007–2008 and the 2 years leading up to the crisis. The highest instantaneous connectedness is detected in the first half of 2006, 2 years prior to the crisis, which provides further empirical evidence for the fact that housing is one of the leading indicators of the business cycle; see Leamer (2007). This finding is different from that of Barigozzi et al. (2021) regarding stock markets where connectedness does not reach a peak until the crisis year 2008.

The heatmap of the long-run connectedness matrix $\hat{\mathbf{Q}}_{n,T}(t; 1)$ is depicted in Figure 2. Compared to the instantaneous connectedness, connectedness in the long run is generally much stronger. At each selected date, different colors in the heatmap suggest that pairwise connectedness exhibits variation across MSAs. In addition, the long-run connectedness varies significantly over time. Similar to the instantaneous connectedness, the long-run connectedness also starts to increase 2 years prior to the financial crisis. However, it remains high afterward.

To focus on the time-varying feature of connectedness, we plot the Frobenius norms of the instantaneous and long-run connectedness matrices in Figure 3. As a reference, we also plot the monthly housing return at the national level. Both the instantaneous and long-run connectedness measures are highly associated with major housing market fluctuations, such as those in the early 1980s and the financial crisis of 2007–2008. Starting in 2019, both measures are on the way up again. During the most recent housing boom associated with the Covid-19 pandemic, housing connectedness turns out to be much stronger compared to the boom period that precedes the 2007 housing market crash.

The connectedness measure can also be constructed for specific frequency bands. We consider frequencies corresponding to cycles of a period of at least 3 years ($\Theta = [0, \pi/18]$, low frequency) and less than 3 years ($\Theta = [\pi/18, \pi]$, high frequency), and report the Frobenius norms⁷ of the spectral connectedness matrix $\hat{\mathbf{Q}}_{n,T}(t; \Theta)$ for these two selected frequency bands in Figure 4. Similar to the instantaneous connectedness, spectral connectedness at the high frequency remains

⁶ Diebold and Yilmaz (2014) show that the variance decomposition framework unifies two important measurements of systemic risk of the financial sector—the CoVaR (the value of risk of the financial system conditional on institutions being under distress) measure of Adrian and Brunnermeier (2011) and the marginal expected shortfall approach of Acharya et al. (2012, 2017).

⁷ The Frobenius norm is matrix norm of an $m \times n$ matrix A defined as the square root of the sum of the absolute squares of its elements, that is, $\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2}$.

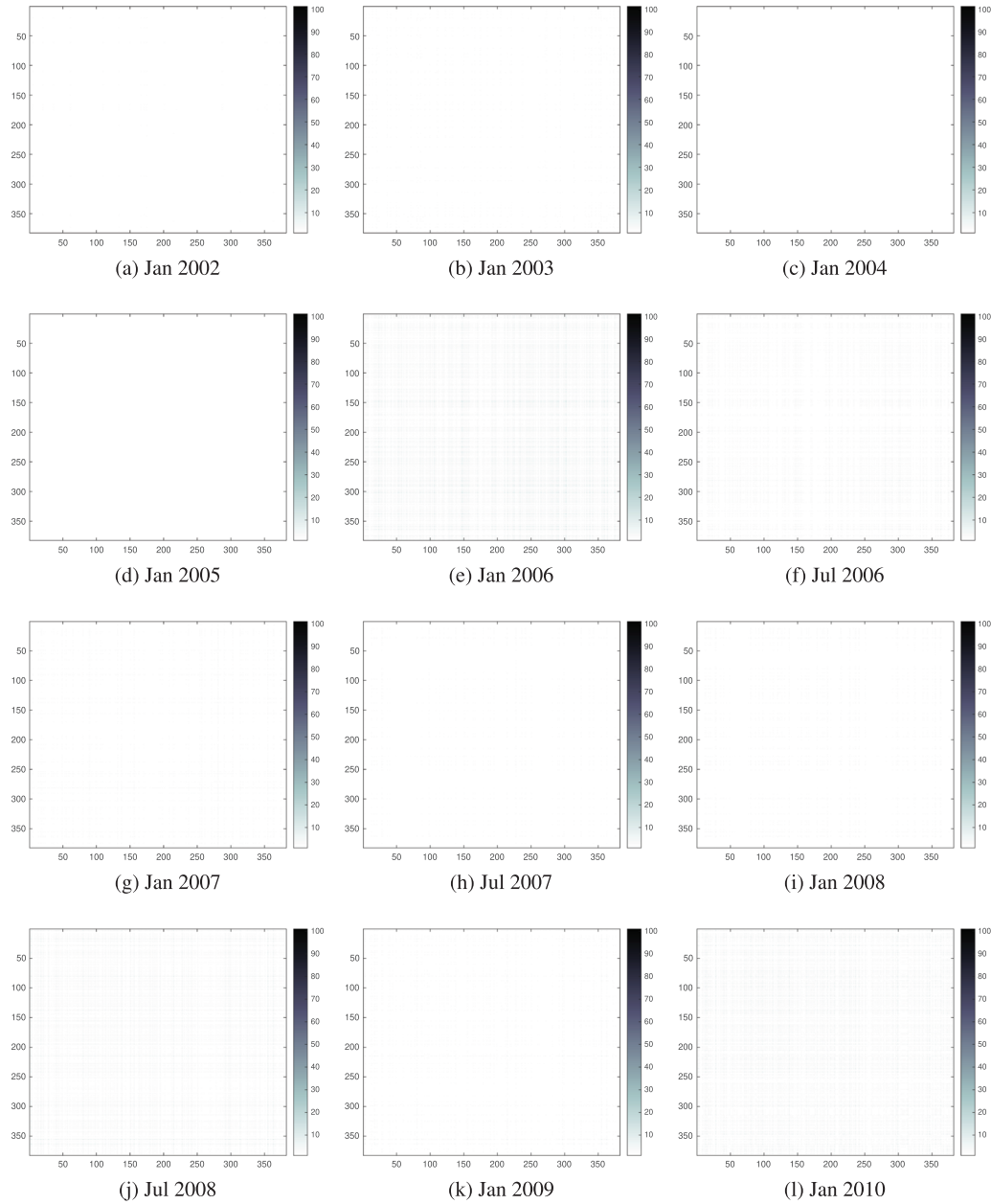


FIGURE 1 Instantaneous connectedness at selected dates [Color figure can be viewed at wileyonlinelibrary.com]

low over the entire sample period except in the early 1980s. The low-frequency spectral connectedness is similar to the connectedness in the long run and exhibits much more variation over time. It spikes in the late 1970s to early 1980s and during the financial crisis of 2007–2008, and remains high in the postcrisis period until 2012.

To illustrate the cross-sectional variation of housing connectedness, we calculate the norm of each column of the connectedness matrices at each point in time and report the MSA-specific

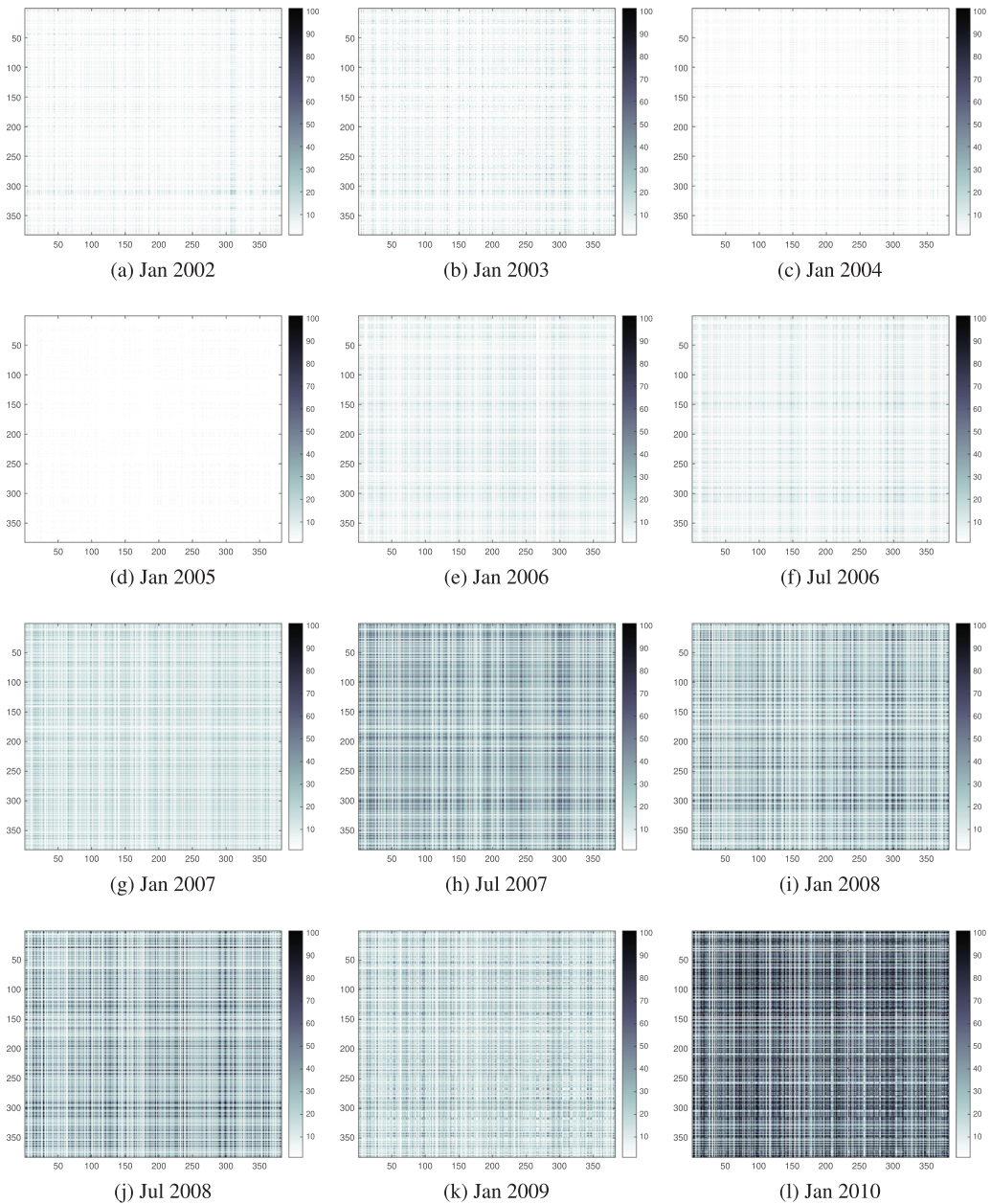


FIGURE 2 Long-run connectedness at selected dates [Color figure can be viewed at wileyonlinelibrary.com]

mean, standard deviation, and the minimum and maximum months in Table A.1 in the Appendix. Local markets with the highest long-run connectedness include Abilene, San Antonio-New Braunfels, Dallas-Fort Worth-Arlington, and Wichita Falls in the state of Texas. At the bottom of the list are metropolitan areas of Beckley, Charleston, Parkersburg-Vienna, and Morgantown in West Virginia. While these MSAs are highly clustered within Texas and West Virginia, a state can also have local markets that differ more in connectedness, such as Gainesville and Naples-Immokalee-Marco Island in Florida. About 50% of the MSAs across the nation reach their peak in the long-run connectedness around 1980, 25% in either 2009 or 2010, and another 20% in 2019.

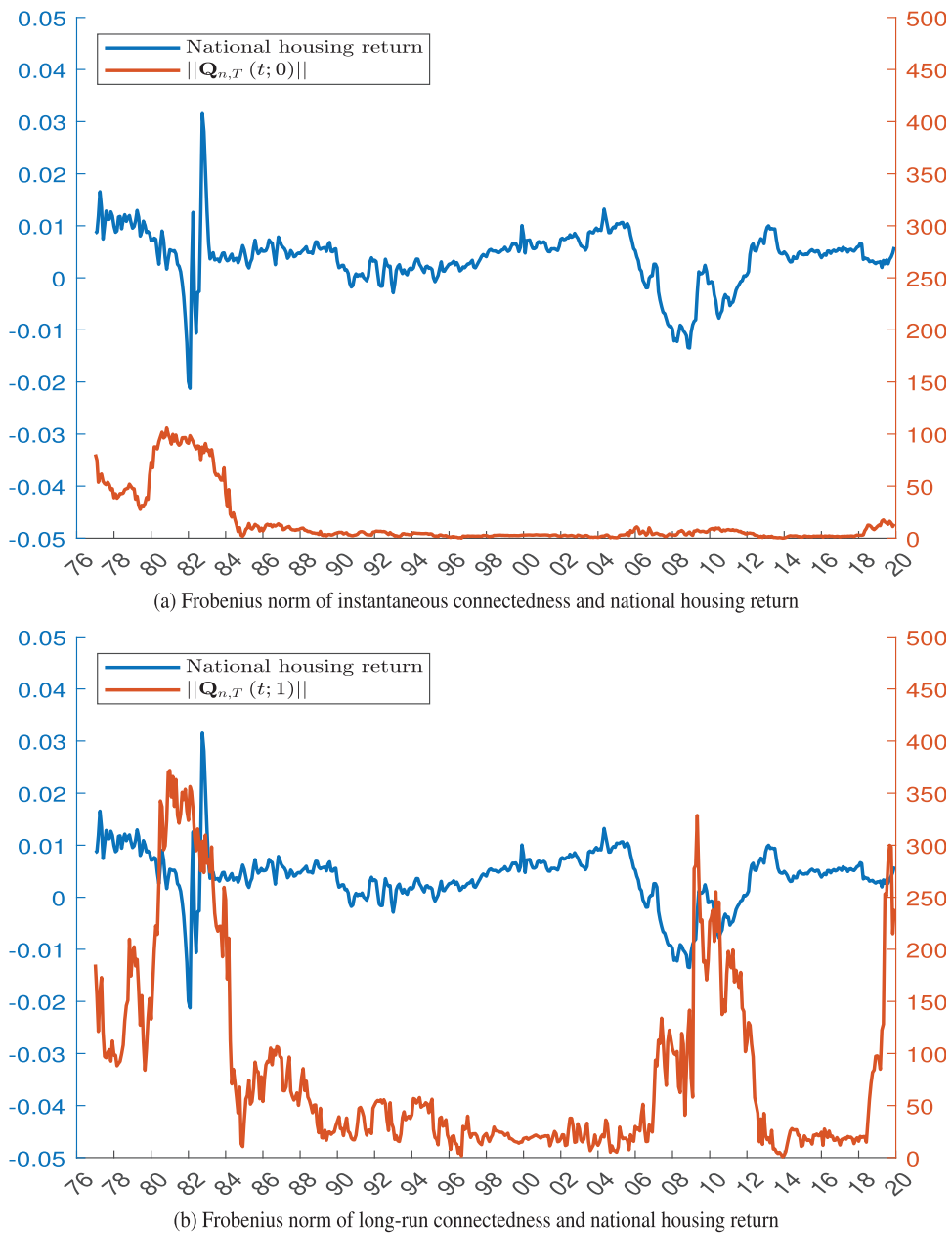


FIGURE 3 Frobenius norm of instantaneous and long-run connectedness [Color figure can be viewed at wileyonlinelibrary.com]

4.2 | In-sample predictive power of housing connectedness

Connectedness in general is of central interest to modern risk measurement and management; it helps quantify the ripple effects and capture key aspects of market risk (Diebold & Yilmaz, 2014). Allowing connectedness to be time-varying by using the method of Barigozzi et al. (2021) enables us to quantify market risk from a dynamic rather than static perspective. As one of the most important sectors over the business cycle, housing has large spillover effects on the

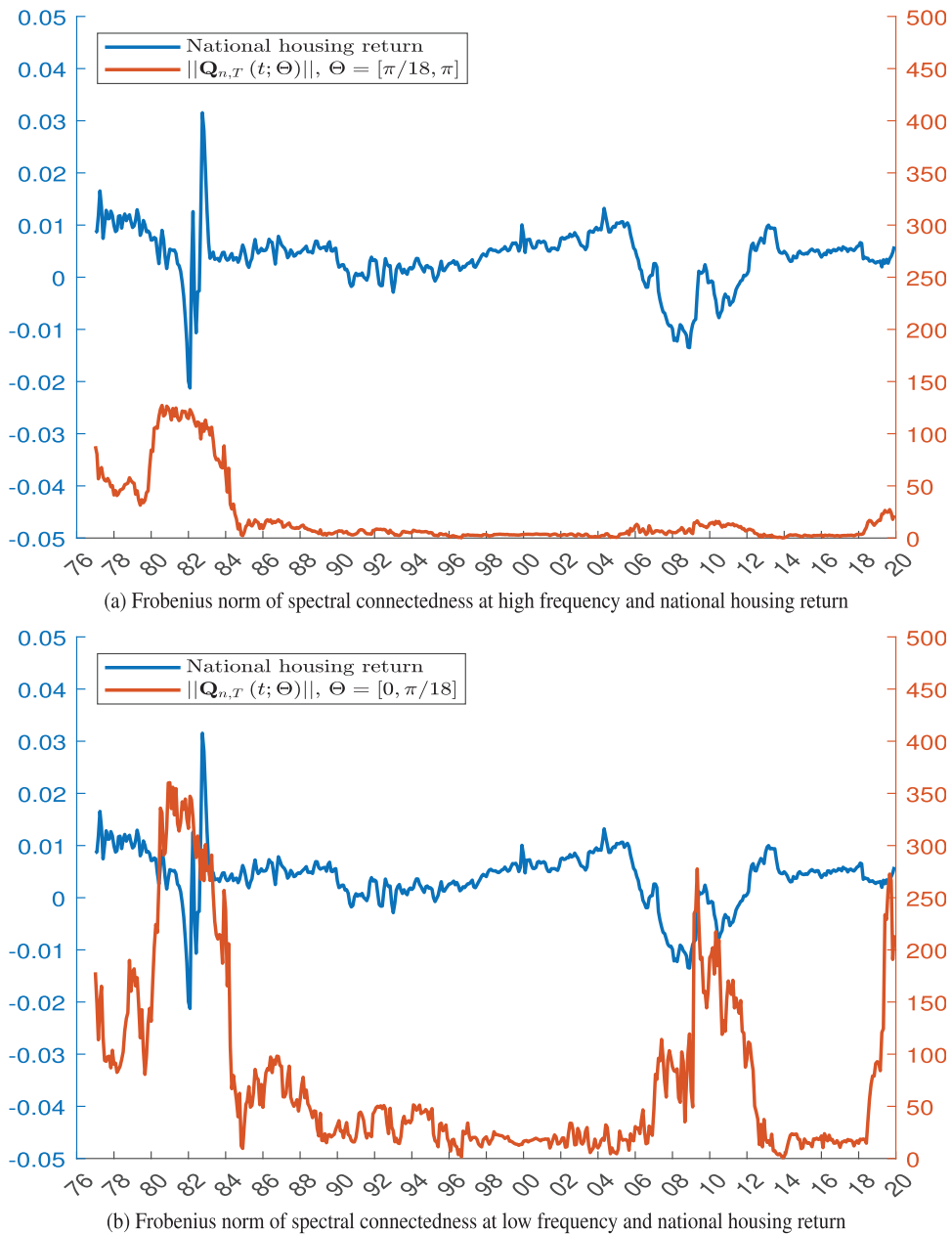


FIGURE 4 Frobenius norm of spectral connectedness [Color figure can be viewed at wileyonlinelibrary.com]

macroeconomy (Iacoviello & Neri, 2010; Leamer, 2007). The spillover effects originate from the fact that housing accounts for the largest source of wealth of American households. At the end of 2021, according to an analysis conducted by Zillow,⁸ the total value of private residential real

⁸See the analysis conducted by Zillow at <https://www.zillow.com/research/us-housing-market-total-value-2021-30615>/<https://www.zillow.com/research/us-housing-market-total-value-2021-30615/>



estate in the United States was \$43.4 trillion, nearly twice the size of the 2021 GDP (about \$23 trillion). For the median U.S. household, housing wealth accounts for about two-thirds of the total wealth. Due to asymmetric effects on collateral constraints, the spillover effects are found to be larger in magnitude during periods of declining house prices compared to periods of rising house prices (Guerrieri & Iacoviello, 2017). Such price declines in the housing market may cause severe recessions. By studying recessions in a cross section of 17 countries over a period of 150 years, Jordà et al. (2015) find that the bursting of a housing bubble, compared to an equity bubble, is more likely to cause more disruptive financial crisis recessions rather than less disruptive normal recessions. It is therefore important to quantify the risk of housing markets and understand its implications on the macroeconomy.

It is well documented in the literature that housing investment leads the business cycle; see Davis and Heathcote (2005). In the previous subsection, we present the first evidence that the connectedness of regional housing markets, in addition to house prices, also leads the business cycle. The time-varying housing connectedness captures important dynamics of the risk of the U.S. housing markets, which may provide warning signs of a recession, given large spillovers from the housing sector to the macroeconomy. In this subsection, we therefore study the predictive power of housing connectedness for future recessions.

A widely used recession predictor is the spread between the long-term and short-term interest rates; see an extensive literature dating back to Harvey (1988, 1989), Stock and Watson (1989), Chen (1991), and Estrella and Hardouvelis (1991) with numerous subsequent studies. Does housing connectedness add any predictive power for future recessions beyond the yield spread? To answer this question, we consider recessions defined by the NBER's Business Cycle Dating Committee and utilize the following Probit specifications:

$$\Pr(R_{t+1,t+h} = 1) = \Phi(\beta_0 + \beta_1 \text{Yield spread}_t + \epsilon_{t+h}), \quad (25)$$

$$\Pr(R_{t+1,t+h} = 1) = \Phi(\beta_0 + \beta_1 \text{Yield spread}_t + \beta_2 \text{Housing return}_t + \epsilon_{t+h}), \quad (26)$$

$$\Pr(R_{t+1,t+h} = 1) = \Phi(\beta_0 + \beta_1 \text{Yield spread}_t + \beta_2 \text{Housing return}_t + \beta_3 \text{Connectedness}_t + \epsilon_{t+h}), \quad (27)$$

where the recession indicator variable $R_{t+1,t+h}$ equals 1 if there is an NBER recession in any period between $t + 1$ and $t + h$, inclusively. Yield spread is the spread between the 10-year and 2-year U.S. Treasury constant maturities, obtained from the Federal Reserve Economic Data. Housing return is the log difference of the national-level house price index from Freddie Mac. Table 2 presents the regression results for prediction horizons of 12, 24, and 36 months.

As in the literature, the spread between the 10-year and 2-year U.S. Treasury yields is a strong predictor of future NBER recessions. As the spread decreases, namely, the yield curve flattens, the likelihood of having a recession over the next 12, 24, or 36 months increases. As a matter of fact, every recession in the United States since 1957 has been preceded by a yield curve inversion. The yield curve reflects investors' expectations of economic growth in the current period compared with economic growth in the future. When investors expect future economic growth to fall behind current economic growth, it indicates that a recession is likely.

Housing return is also a significant predictor of future recessions, particularly at shorter horizons. As the housing return decreases, the likelihood of future recessions increases. Controlling

TABLE 2 In-sample predictive power of housing connectedness for future NBER recessions

Horizon $h = 12$	(1)	(2)	(3)	(4)
Yield spread	−0.740***	−1.035***	−0.958***	−1.071***
	(−4.016)	(−5.053)	(−3.911)	(−4.234)
Housing return		−1.204***	−1.437***	−1.266***
		(−2.641)	(−3.095)	(−2.697)
Instantaneous connectedness			0.018***	
			(3.181)	
Long-run connectedness				0.006***
				(3.332)
Observations	536	536	516	516
Adjusted R^2	0.167	0.311	0.364	0.394
Horizon $h = 24$	(1)	(2)	(3)	(4)
Yield spread	−1.177***	−1.510***	−1.548***	−1.652***
	(−4.998)	(−6.449)	(−5.578)	(−5.820)
Housing return		−1.144**	−1.411***	−1.236***
		(−2.486)	(−3.094)	(−2.880)
Instantaneous connectedness			0.017**	
			(2.150)	
Long-run connectedness				0.005**
				(2.454)
Observations	524	524	516	516
Adjusted R^2	0.318	0.417	0.446	0.461
Horizon $h = 36$	(1)	(2)	(3)	(4)
Yield spread	−1.264***	−1.353***	−1.339***	−1.386***
	(−6.644)	(−8.297)	(−7.969)	(−8.715)
Housing return		−0.450	−0.572*	−0.446
		(−1.370)	(−1.753)	(−1.443)
Instantaneous connectedness			0.010	
			(1.387)	
Long-run connectedness				0.003
				(1.407)
Observations	512	512	505	505
Adjusted R^2	0.345	0.363	0.375	0.373

Note: Entries in parentheses are t statistics constructed using Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

for the yield spread and housing return, both the instantaneous and long-run housing connectedness measures remain a significant predictor of future recessions at shorter horizons. The likelihood of having a recession over the next 1–2 years is heightened as housing connectedness increases. The intuition of this result is straightforward. An increase in connectedness indicates a synergistic movement of regional housing markets. Synergistic declines of regional housing markets are more likely to be associated with recessions.

**TABLE 3** Out-of-sample predictive power of housing connectedness for future NBER recessions

Predictors	2007M1–2022M1	2012M1–2022M1	2017M1–2022M1
Yield spread	0.121	0.071	0.170
Yield spread + Housing return	0.096	0.063	0.158
	(0.79)	(0.89)	(0.93)
Yield spread + Housing return	0.079	0.020	0.042
+ Instantaneous connectedness	(0.65)	(0.28)	(0.25)
Yield spread + Housing return	0.083	0.022	0.040
+ Long-run connectedness	(0.69)	(0.31)	(0.24)

Note: The table reports the mean-squared prediction error at the 36-month horizon. Ratios with respect to the benchmark model with the yield spread as the only predictor are in parentheses.

4.3 | Out-of-sample predictive power of housing connectedness

While Table 2 shows that the in-sample fitting of the Probit model is improved after accounting for housing connectedness measures, whether or not one can use housing connectedness in practice to predict recessions depends on the out-of-sample performance. Using the housing connectedness measure to predict future recessions is complicated by a computational lag. As Barigozzi et al. (2021) point out, the connectedness measure can only be computed for the central ($T - M_T + 1$) time points of the sample. In other words, at any point in time, the connectedness measure that is available is from $M_T/2$ periods ago. We therefore lag the connectedness measure in Equation (27) by $M_T/2$ periods and generate projections on the likelihood of recessions 36 months ahead. Due to the computational lag, projections at any horizons less than or equal to $M_T/2$ months (or 24 months in this study) are not available. We split the entire sample into an estimation sample and an evaluation sample that are mutually complementary. Table 3 evaluates each specification's predictive performance using the mean-squared prediction error for three evaluation samples starting in January 2007, January 2012, and January 2017, respectively.

Compared to the benchmark model where the yield spread is the only recession predictor, adding the national housing return as an additional predictor reduces the mean-squared prediction error by 21% between 2007M1 and 2022M1, a sample period that covers the Great Recession. Further adding the instantaneous or long-run housing connectedness yields a reduction of the mean-squared prediction error by another 10–14%. Over the past 10 years, accounting for housing connectedness may reduce the mean-squared prediction error by as much as 70%.

5 | CONCLUSION

While the literature on the role of price diffusion or ripple effects across housing markets and corresponding convergence in regional house prices has been extensively examined, this study extends this literature through the use of high-dimensional time-varying connectedness of housing markets. Specifically, we study the time-varying connectedness of housing markets across 382 metropolitan areas in the United States and find that housing connectedness in the long run is much stronger than in the short run. Both instantaneous and long-run connectedness measures are associated with major housing market fluctuations, and they lead the business cycle and help predict the likelihood of future NBER recessions.

Whether the economy is in an expansion or recession effects, the level of activity in real estate markets and the performance of real estate investment trusts. Predicting future recessions therefore has important implications for researchers in both academia and those in the residential and commercial real estate sectors. Leading indicators provide valuable information about the onset and end of recessions. The widely used recession predictor, that is, the yield spread, being controlled, the connectedness of local housing markets significantly improves the predictive accuracy.

Our analysis can be readily applied to metropolitan housing markets in other countries to further test the robustness of our findings. Moreover, while we focus on residential housing markets, our analysis can be extended to the commercial real estate market as well.

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TABLE A.1 MSA housing connectedness

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Abilene TX	1.909	3.853	1996M7	1980M11	5.971	10.575	1996M7	1980M12
Akron OH	0.737	1.351	1988M8	1981M3	4.819	7.049	2013M12	1980M12
Albany GA	0.402	0.352	2013M12	1977M4	3.372	4.411	2013M12	2010M5
Albany OR	0.273	0.239	2013M12	1986M10	4.231	4.420	2013M12	2009M5
Albany–Schenectady–Troy NY	0.450	0.892	1996M2	1983M4	3.261	3.235	2013M10	1984M1
Albuquerque NM	0.178	0.189	2004M2	1979M10	2.248	2.305	2013M12	1980M4
Alexandria LA	0.260	0.288	1996M2	1982M3	3.209	3.658	1996M9	2019M9
Allentown–Bethlehem–Easton PA–NJ	0.337	0.386	2013M12	1977M5	3.463	3.443	2013M12	2019M9
Altoona PA	0.457	0.607	1996M9	1977M5	3.490	4.006	1996M9	2019M9
Amarillo TX	1.705	3.486	2014M2	1980M11	5.581	9.959	2014M2	1982M2
Ames IA	0.277	0.306	2007M7	1984M1	3.407	5.202	2013M12	1978M11
Anchorage AK	0.133	0.163	2014M1	1985M4	2.092	2.431	2014M1	1992M1
Ann Arbor MI	0.514	0.674	1987M11	1984M3	4.080	5.143	1996M9	2009M5
Anniston–Oxford–Jacksonville AL	0.362	0.385	2013M11	1982M3	3.693	4.165	1998M3	2019M9
Appleton WI	0.791	1.752	2013M12	1980M8	4.829	7.985	1996M2	1980M8
Asheville NC	0.696	1.196	2013M12	1981M3	4.348	6.044	2013M12	2019M9
Athens–Clarke County GA	0.338	0.306	2013M12	1977M4	3.184	4.554	2003M8	2010M5
Atlanta–Sandy Springs–Roswell GA	0.324	0.289	2014M2	1977M4	3.260	4.988	2013M12	2010M5
Atlantic City–Hammonton NJ	0.221	0.243	2013M12	1980M11	2.885	2.999	2013M12	1980M12
Auburn–Opelika AL	0.362	0.379	2013M12	1982M11	3.249	3.599	2013M10	2019M9
Augusta–Richmond County GA–SC	0.490	0.611	2013M12	1981M6	4.139	5.183	1977M10	2019M9
Austin–Round Rock TX	1.480	2.986	1996M9	1980M11	5.573	8.279	1996M7	1982M2
Bakersfield CA	0.803	1.874	1996M9	1980M8	3.544	3.643	2013M12	2009M5
Baltimore–Columbia–Towson MD	0.420	0.524	2013M12	1984M1	3.218	3.536	2018M3	2009M5
Bangor ME	0.153	0.168	2008M7	1979M4	2.274	2.529	1996M2	2019M10
Barnstable Town MA	0.231	0.246	2013M12	1979M12	2.430	2.491	2004M3	2019M9
Baton Rouge LA	0.233	0.245	2002M10	1982M12	2.834	3.016	1996M9	2019M9
Battle Creek MI	0.543	0.724	2013M12	1983M12	3.705	5.158	2003M8	2009M5
Bay City MI	0.540	0.728	2003M8	1983M12	3.847	5.510	1996M9	2009M5
Beaumont–Port Arthur TX	1.721	3.497	2014M2	1980M11	5.642	10.378	2014M2	1981M5
Beckley WV	0.145	0.175	2013M12	1979M10	1.598	2.013	2013M12	1981M1
Bellingham WA	0.868	2.052	1996M9	1980M11	4.612	6.548	2013M12	1981M3
Bend–Redmond OR	0.227	0.195	2013M12	1986M11	3.411	3.987	1987M10	2009M5
Billings MT	0.243	0.287	2007M6	1980M11	2.648	3.128	2004M9	2019M9
Binghamton NY	0.452	0.959	2008M1	1982M2	3.191	3.507	2013M12	1984M1
Birmingham–Hoover AL	0.381	0.396	2013M12	1982M4	3.515	4.140	2013M9	1979M4
Bismarck ND	0.158	0.219	1996M9	1980M1	1.785	1.817	2013M10	2019M9
Blacksburg–Christiansburg–Radford VA	0.526	0.724	2004M9	1982M12	4.688	5.810	2006M10	1981M5
Bloomington IL	0.670	1.164	2013M12	1984M3	2.478	2.943	2013M12	2019M9
Bloomington IN	0.474	0.810	2013M11	1983M2	3.243	4.189	2014M1	1980M7

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Bloomsburg–Berwick PA	0.455	0.598	1996M7	1977M5	3.263	3.592	2013M11	2019M9
Boise City ID	0.204	0.183	1996M9	2019M4	2.710	2.854	2003M10	2019M12
Boston–Cambridge–Newton MA–NH	0.270	0.284	2013M12	1979M12	3.095	3.013	2013M12	2009M5
Boulder CO	0.535	0.813	2013M12	1981M5	4.558	4.695	2013M12	2009M5
Bowling Green KY	0.330	0.351	1996M9	1979M10	3.493	4.062	2014M2	2019M9
Bremerton–Silverdale WA	0.866	2.046	1996M9	1980M12	4.482	6.568	1997M4	1980M12
Bridgeport–Stamford–Norwalk CT	0.192	0.176	2013M10	1980M7	2.777	2.563	1983M9	2009M5
Brownsville–Harlingen TX	1.727	3.516	1996M9	1980M11	5.541	10.190	1996M9	1981M3
Brunswick GA	0.310	0.279	2013M12	2019M5	3.073	4.540	2014M1	2010M5
Buffalo–Cheektowaga–Niagara Falls NY	0.548	1.131	1996M2	1981M11	3.335	4.189	2005M7	1982M4
Burlington NC	0.637	1.138	2004M1	1980M11	4.396	5.874	2013M12	2019M10
Burlington–South Burlington VT	0.179	0.192	2014M1	1977M1	3.091	3.115	1996M2	2019M10
California–Lexington Park MD	0.395	0.478	2013M12	1980M7	3.210	3.651	2013M12	2009M5
Canton–Massillon OH	0.758	1.394	2013M12	1980M12	4.791	7.324	1996M9	1981M1
Cape Coral–Fort Myers FL	0.748	1.426	2014M1	1977M1	3.286	3.929	2013M12	2009M5
Cape Girardeau MO–IL	0.714	1.843	2013M12	1977M1	2.566	3.794	2013M12	1977M1
Carbondale–Marion IL	0.690	1.204	1996M9	1984M3	2.300	2.850	1980M9	2019M9
Carson City NV	0.129	0.137	1996M9	2006M1	2.697	4.222	1983M10	2009M5
Casper WY	0.182	0.205	2013M10	1982M4	2.517	2.623	2014M1	1984M1
Cedar Rapids IA	0.305	0.326	2014M1	1980M1	3.095	3.810	2002M2	1978M11
Chambersburg–Waynesboro PA	0.340	0.453	1996M9	1977M5	2.807	3.296	2013M12	1979M2
Champaign–Urbana IL	0.674	1.167	2013M12	1978M12	2.438	3.013	2013M12	2019M8
Charleston WV	0.133	0.170	2013M12	1979M10	1.609	2.124	2013M12	1980M12
Charleston–North Charleston SC	0.531	0.928	2013M12	1981M12	4.094	5.285	2013M12	1984M1
Charlotte–Concord–Gastonia NC–SC	0.661	1.152	2004M2	1981M5	4.590	6.193	2013M12	1981M3
Charlottesville VA	0.449	0.597	1996M9	1983M2	4.611	4.946	2013M12	1981M10
Chattanooga TN–GA	0.752	1.655	1977M11	1980M11	4.123	6.508	2014M2	1980M12
Cheyenne WY	0.253	0.308	2013M12	1982M4	2.988	3.106	1996M8	1979M4
Chicago–Naperville–Elgin IL–IN–WI	0.560	0.930	1980M2	1984M3	2.991	3.522	2016M7	2009M3
Chico CA	0.922	2.196	2016M11	1980M8	4.010	3.828	1996M9	1980M7
Cincinnati OH–KY–IN	0.716	1.258	1988M7	1980M11	4.957	6.716	2013M12	1981M1
Clarksville TN–KY	0.772	1.614	2013M7	1982M4	4.052	6.293	2013M11	1981M3
Cleveland TN	0.789	1.761	2013M12	1981M5	4.321	7.288	1996M9	1981M5
Cleveland–Elyria OH	0.697	1.326	1996M9	1980M6	4.588	6.942	2006M8	1980M12
Coeur d’Alene ID	0.203	0.176	2013M12	2019M4	2.841	2.632	2013M12	2019M12
College Station–Bryan TX	1.828	3.717	1996M9	1980M11	5.763	10.123	2004M1	1981M5
Colorado Springs CO	0.497	0.740	2013M12	1980M7	4.324	4.919	2013M12	2009M5
Columbia MO	0.705	1.848	1990M12	1977M1	2.542	3.986	1984M12	1977M4
Columbia SC	0.577	1.054	2013M12	1982M2	3.942	6.209	2013M12	1984M1
Columbus GA–AL	0.400	0.335	2013M12	1977M4	3.206	4.274	2013M12	2009M5

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Columbus IN	0.466	0.820	2013M12	1983M2	3.337	4.294	2006M8	1980M7
Columbus OH	0.792	1.474	2013M12	1980M6	4.836	6.970	2013M12	1981M3
Corpus Christi TX	1.721	3.483	1996M9	1980M11	5.711	9.538	1984M12	1981M3
Corvallis OR	0.285	0.255	2005M1	1986M10	4.000	3.931	1977M11	2009M5
Crestview–Fort Walton Beach–Destin FL	0.835	1.616	2014M1	1977M1	3.552	4.188	2014M1	2009M5
Cumberland MD–WV	0.414	0.518	2013M7	1980M7	3.302	2.959	2013M8	2019M10
Dallas–Fort Worth–Arlington TX	1.639	3.316	1996M9	1980M11	5.783	9.757	1996M9	1981M1
Dalton GA	0.352	0.318	2013M12	1977M4	3.326	4.957	2013M12	2010M5
Danville IL	0.661	1.139	2018M3	1978M12	2.558	3.199	2013M12	1980M7
Daphne–Fairhope–Foley AL	0.281	0.286	2013M10	1982M11	2.899	3.149	1998M3	2019M9
Davenport–Moline–Rock Island IA–IL	0.436	0.620	2013M12	1978M12	2.637	2.844	1996M9	2019M9
Dayton OH	0.754	1.412	2013M12	1980M11	5.045	7.244	2013M12	1980M12
Decatur AL	0.342	0.347	2013M11	1982M11	3.357	3.766	2013M11	2019M9
Decatur IL	0.564	0.982	2018M3	1984M3	2.167	2.901	1983M7	1980M7
Deltona–Daytona Beach–Ormond Beach FL	0.807	1.581	2013M11	1977M1	3.576	4.198	1988M7	2009M5
Denver–Aurora–Lakewood CO	0.498	0.755	2013M12	1981M5	4.434	5.177	2003M5	2009M5
Des Moines–West Des Moines IA	0.292	0.304	2013M12	1984M1	3.468	4.616	2013M12	1978M11
Detroit–Warren–Dearborn MI	0.472	0.608	2013M12	1983M12	4.211	5.753	2013M12	2009M5
Dothan AL	0.405	0.452	2013M11	1982M11	3.470	3.724	2013M12	1979M4
Dover DE	0.253	0.325	2013M12	1981M3	2.554	2.448	2013M12	2009M5
Dubuque IA	0.279	0.300	2013M12	1980M1	2.921	3.533	2013M12	1978M11
Duluth MN–WI	0.739	1.544	1996M8	1982M3	4.277	6.874	1991M3	1981M11
Durham–Chapel Hill NC	0.711	1.251	2013M12	1980M11	4.724	6.307	2004M1	2019M8
East Stroudsburg PA	0.310	0.381	1996M9	1977M5	3.019	3.250	2013M12	2019M8
Eau Claire WI	0.724	1.569	2013M12	1980M8	4.735	8.018	1990M11	1980M8
El Centro CA	0.861	2.042	1988M5	1980M8	3.509	3.906	2006M10	2009M5
El Paso TX	1.751	3.520	2014M2	1980M11	5.713	9.543	2014M2	1982M2
Elizabethtown–Fort Knox KY	0.327	0.334	1996M9	2019M5	3.535	4.133	2014M2	2019M9
Elkhart–Goshen IN	0.448	0.739	2014M2	1982M8	3.657	4.530	2013M11	2009M5
Elmira NY	0.542	1.083	1996M9	1982M3	3.271	4.174	2013M9	1982M3
Enid OK	0.159	0.189	2004M3	1979M1	2.524	3.223	2013M12	1984M1
Erie PA	0.477	0.609	1996M7	1977M4	2.985	3.412	2013M10	2019M10
Eugene OR	0.280	0.247	2013M12	1986M10	3.884	4.295	2013M12	2009M5
Evansville IN–KY	0.499	0.841	2013M10	1982M5	3.544	4.558	2013M12	2009M5
Fairbanks AK	0.132	0.163	2013M12	1985M4	2.056	2.459	2013M12	1981M3
Fargo ND–MN	0.399	0.798	2018M3	1981M5	3.783	5.862	1984M12	1981M10
Farmington NM	0.190	0.198	2013M12	1979M10	2.186	2.271	1984M12	2019M8
Fayetteville NC	0.736	1.269	2013M12	1982M3	4.356	6.194	2018M6	2019M9
Fayetteville–Springdale–Rogers AR–MO	0.172	0.200	2013M12	1977M1	2.365	3.096	2000M4	2009M5
Flagstaff AZ	0.449	0.812	2013M12	1982M4	3.879	4.762	2013M11	1984M1

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Flint MI	0.496	0.640	2013M12	1984M3	4.041	5.745	1987M11	2009M5
Florence SC	0.641	1.160	2013M12	1982M2	4.158	6.579	2004M9	1984M1
Florence–Muscle Shoals AL	0.374	0.395	2013M12	1982M11	3.541	4.096	2013M12	2019M9
Fond du Lac WI	0.732	1.556	2008M3	1980M11	4.927	7.755	1996M8	1980M7
Fort Collins CO	0.540	0.817	1984M12	1981M3	4.499	4.665	2002M10	2009M5
Fort Smith AR–OK	0.187	0.209	2014M2	1977M1	2.388	2.721	1999M5	2019M7
Fort Wayne IN	0.435	0.741	2014M2	1983M12	3.423	4.316	2014M2	1984M1
Fresno CA	0.852	1.986	2013M12	1980M8	3.604	3.752	1988M7	2009M5
Gadsden AL	0.350	0.393	2013M12	1982M11	3.247	3.646	2013M12	2019M9
Gainesville FL	0.934	1.835	2014M1	1977M1	4.008	4.831	2013M12	2009M5
Gainesville GA	0.317	0.273	2004M3	1984M7	3.117	4.633	1996M9	2019M10
Gettysburg PA	0.381	0.479	1996M9	1977M5	3.232	3.592	2001M6	2009M5
Glens Falls NY	0.479	0.932	1996M2	1982M5	3.550	3.647	2013M12	1982M5
Goldsboro NC	0.691	1.194	2013M12	1980M11	4.318	6.231	2003M10	2019M10
Grand Forks ND–MN	0.402	0.750	2013M12	1983M12	3.630	5.587	1987M8	1981M3
Grand Island NE	0.203	0.178	2013M12	2019M5	2.621	2.950	1980M6	2019M10
Grand Junction CO	0.400	0.620	2005M2	1981M5	3.508	3.938	2013M12	2009M5
Grand Rapids–Wyoming MI	0.562	0.729	2013M12	1983M12	4.129	5.529	2004M1	2009M5
Grants Pass OR	0.260	0.231	2013M12	1986M10	3.584	4.237	2013M12	2009M5
Great Falls MT	0.278	0.325	2013M12	1980M11	3.317	4.193	2013M12	2019M9
Greeley CO	0.495	0.762	2013M12	1981M3	4.252	4.960	2014M1	2009M5
Green Bay WI	0.717	1.543	2013M12	1980M10	4.678	7.348	2013M12	1980M8
Greensboro–High Point NC	0.723	1.254	2013M12	1980M11	4.531	6.305	2003M10	1980M12
Greenville NC	0.699	1.253	2004M1	1982M2	4.491	6.345	2013M12	1981M1
Greenville–Anderson–Mauldin SC	0.593	1.091	1984M12	1981M11	4.113	6.564	2003M8	1984M1
Gulfport–Biloxi–Pascagoula MS	0.288	0.457	2008M7	1980M12	2.593	3.506	2013M12	1981M3
Hagerstown–Martinsburg MD–WV	0.308	0.356	2018M3	1980M7	2.732	3.210	2013M9	2009M5
Hammond LA	0.222	0.247	1996M7	2006M2	2.556	2.817	1999M5	1986M10
Hanford–Corcoran CA	0.885	2.087	2013M12	1980M8	3.706	3.769	2013M12	2009M5
Harrisburg–Carlisle PA	0.454	0.591	2013M12	1977M5	3.147	3.593	2013M12	2019M10
Harrisonburg VA	0.493	0.629	1998M5	1982M11	4.806	5.206	1998M5	2009M5
Hartford–West Hartford–East Hartford CT	0.217	0.215	2014M2	1980M7	2.930	2.729	2018M3	1980M7
Hattiesburg MS	0.317	0.526	1996M9	1980M8	2.368	3.651	2013M12	1980M8
Hickory–Lenoir–Morganton NC	0.670	1.152	2013M12	1981M5	4.426	5.959	2003M12	2019M10
Hilton Head Island–Bluffton–Beaufort SC	0.494	0.843	2007M9	1982M5	3.909	5.057	2013M12	1982M3
Hinesville GA	0.370	0.325	2014M2	1983M3	3.647	4.363	2013M12	2019M10
Homosassa Springs FL	0.811	1.566	2013M12	1977M1	3.544	3.939	2013M12	2009M5
Hot Springs AR	0.182	0.211	2013M12	1977M1	2.114	2.324	2013M12	2019M8
Houma–Thibodaux LA	0.245	0.275	2013M12	1982M12	2.883	3.122	2018M3	1984M1
Houston–The Woodlands–Sugar Land TX	1.733	3.466	1996M9	1980M12	5.768	9.236	1984M12	1982M2

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Huntington–Ashland WV–KY–OH	0.189	0.222	2014M1	1979M10	2.017	2.252	2014M1	1982M10
Huntsville AL	0.336	0.350	2013M11	1982M3	3.086	3.503	2013M9	2019M10
Idaho Falls ID	0.219	0.200	2013M12	2019M4	2.647	3.034	2013M12	2019M11
Indianapolis–Carmel–Anderson IN	0.492	0.838	2013M10	1982M8	3.553	4.853	1984M12	1984M1
Iowa City IA	0.315	0.347	2014M1	1984M1	3.470	4.700	2013M12	1978M11
Ithaca NY	0.493	1.008	2013M9	1982M8	3.376	3.726	2013M10	1984M1
Jackson MI	0.503	0.655	2013M12	1984M3	4.254	5.257	2014M1	2009M3
Jackson MS	0.320	0.531	1996M7	1980M11	2.336	3.689	1996M9	1980M12
Jackson TN	0.721	1.619	1991M1	1980M11	3.996	6.474	2013M11	1981M3
Jacksonville FL	0.906	1.778	2004M2	1977M1	3.727	4.496	2013M12	2009M4
Jacksonville NC	0.595	1.031	2013M12	1980M11	4.031	5.240	1984M12	2019M9
Janesville–Beloit WI	0.743	1.592	2013M12	1981M1	5.242	7.817	1996M9	1980M8
Jefferson City MO	0.674	1.772	2013M12	1977M1	2.598	3.885	2013M12	1977M1
Johnson City TN	0.816	1.839	2013M8	1981M5	4.177	6.658	1996M9	1981M10
Johnstown PA	0.421	0.566	1996M7	1977M5	2.966	3.262	1996M9	2019M10
Jonesboro AR	0.189	0.227	2005M9	1977M1	2.169	2.852	2013M12	2019M8
Joplin MO	0.662	1.764	2013M12	1977M2	2.595	4.196	2013M12	1980M7
Kahului–Wailuku–Lahaina HI	0.242	0.501	2016M2	1980M8	1.859	2.927	1996M9	1979M10
Kalamazoo–Portage MI	0.577	0.791	1996M9	1983M12	3.927	5.297	2003M8	1982M3
Kankakee IL	0.647	1.103	2018M3	1984M3	2.887	2.900	2013M12	1980M7
Kansas City MO–KS	0.509	1.274	2007M9	1977M1	2.563	4.027	2013M12	2009M5
Kennewick–Richland WA	0.884	2.104	1997M10	1980M9	4.274	6.564	2013M12	1980M9
Killeen–Temple TX	1.708	3.446	2014M2	1980M11	5.644	9.724	2014M2	1981M5
Kingsport–Bristol–Bristol TN–VA	0.749	1.585	2014M1	1982M2	4.567	6.994	2013M12	1981M1
Kingston NY	0.376	0.744	1996M2	1982M4	3.094	3.028	2013M10	2019M10
Knoxville TN	0.763	1.730	1991M1	1982M2	4.156	6.760	2014M1	1981M3
Kokomo IN	0.438	0.752	2013M11	1981M5	3.319	4.298	2013M11	1980M7
La Crosse–Onalaska WI–MN	0.822	1.785	1990M12	1980M10	5.233	8.746	2013M12	1981M1
Lafayette LA	0.204	0.238	2002M11	1982M12	2.850	3.292	2002M11	1984M1
Lafayette–West Lafayette IN	0.490	0.857	2013M10	1983M2	3.527	4.638	2013M12	1980M7
Lake Charles LA	0.245	0.274	1996M9	1982M12	2.963	3.073	1996M7	1984M1
Lake Havasu City–Kingman AZ	0.402	0.730	1996M8	1982M3	3.393	4.053	2013M12	1982M3
Lakeland–Winter Haven FL	0.835	1.630	2013M11	1977M1	3.638	4.159	2013M12	1977M1
Lancaster PA	0.400	0.522	1996M9	1977M5	3.447	3.727	2013M12	2019M9
Lansing–East Lansing MI	0.562	0.726	2003M8	1983M12	4.251	5.771	2013M12	2009M5
Laredo TX	1.752	3.550	1996M9	1980M11	5.773	10.031	2014M2	1981M1
Las Cruces NM	0.190	0.196	2013M12	1979M10	2.028	2.152	2002M4	2019M8
Las Vegas–Henderson–Paradise NV	0.118	0.137	1996M9	2006M10	2.478	3.786	1996M9	2009M5
Lawrence KS	0.322	0.387	2007M6	1980M1	3.219	4.342	1996M9	2009M5
Lawton OK	0.217	0.260	2013M12	1977M2	2.445	3.064	2014M1	1979M12

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Lebanon PA	0.349	0.449	1996M7	1977M5	3.177	3.618	2013M10	1979M4
Lewiston ID-WA	0.641	1.245	1997M10	1980M12	4.666	5.313	2002M10	1981M3
Lewiston-Auburn ME	0.143	0.163	2013M10	1980M1	2.269	2.633	2013M11	2019M10
Lexington-Fayette KY	0.313	0.315	2013M8	1979M10	3.451	4.049	2014M2	2019M9
Lima OH	0.785	1.460	1996M9	1980M11	4.648	7.008	2006M8	1981M1
Lincoln NE	0.219	0.183	2013M12	2019M5	2.393	3.131	2013M12	2019M8
Little Rock-North Little Rock-Conway AR	0.184	0.223	2013M12	1977M1	2.257	2.756	2014M2	1977M4
Logan UT-ID	0.235	0.267	2013M12	2019M5	2.675	2.907	1990M9	2019M10
Longview TX	1.810	3.667	1996M8	1980M11	5.722	10.090	1996M7	1981M11
Longview WA	0.849	2.003	2013M12	1980M8	4.429	6.573	2013M12	1981M9
Los Angeles-Long Beach-Anaheim CA	0.799	1.881	2013M12	1980M8	3.289	3.286	1990M12	2009M5
Louisville/Jefferson County KY-IN	0.438	0.504	2013M10	1980M11	3.995	4.828	2013M11	2019M10
Lubbock TX	1.821	3.715	1996M9	1980M11	5.667	10.922	2014M2	1981M3
Lynchburg VA	0.534	0.700	2004M9	1982M11	4.689	5.423	1977M9	1981M5
Macon GA	0.429	0.395	2013M12	1977M4	3.350	4.768	2014M1	2019M9
Madera CA	0.812	1.917	1996M9	1980M8	3.679	3.647	2013M12	2009M5
Madison WI	0.828	1.797	2013M12	1981M1	5.348	8.437	1996M8	1981M1
Manchester-Nashua NH	0.175	0.152	2002M10	1983M5	2.426	2.525	1996M9	2009M5
Manhattan KS	0.341	0.394	2013M8	1980M1	3.088	4.050	1988M8	2009M5
Mankato-North Mankato MN	0.668	1.405	1996M8	1982M3	3.920	6.482	2013M12	1981M9
Mansfield OH	0.750	1.388	2013M12	1980M10	4.273	6.631	1988M5	1981M1
McAllen-Edinburg-Mission TX	1.814	3.662	1996M9	1980M11	5.768	10.086	2013M7	1982M2
Medford OR	0.245	0.214	2013M12	1986M11	3.607	4.180	2013M12	2009M5
Memphis TN-MS-AR	0.649	1.418	2013M7	1980M12	4.122	6.993	2013M12	1981M3
Merced CA	0.715	1.661	1996M9	1980M8	3.292	3.307	2014M1	2009M5
Miami-Fort Lauderdale-West Palm Beach FL	0.808	1.580	2013M12	1977M1	3.897	4.685	2013M12	2009M5
Michigan City-La Porte IN	0.369	0.615	2013M11	1984M1	2.851	3.580	1987M2	1980M7
Midland MI	0.599	0.828	2013M12	1980M11	3.745	5.158	1996M9	1982M7
Midland TX	1.479	3.017	1996M9	1980M11	5.331	9.009	2013M9	1980M12
Milwaukee-Waukesha-West Allis WI	0.764	1.657	1993M10	1980M10	5.221	8.401	1996M9	1981M1
Minneapolis-St. Paul-Bloomington MN-WI	0.687	1.397	2013M12	1982M2	4.230	6.154	1996M9	1982M3
Missoula MT	0.216	0.247	1990M12	1980M1	2.788	3.099	2013M12	2019M9
Mobile AL	0.331	0.360	2013M12	1982M11	3.214	3.360	2013M12	2010M2
Modesto CA	0.731	1.701	2013M12	1980M8	3.341	3.276	2006M11	2009M5
Monroe LA	0.277	0.304	1996M7	2019M5	2.648	3.068	2018M3	2019M9
Monroe MI	0.528	0.685	2013M12	1983M12	4.075	5.709	2013M12	2009M5
Montgomery AL	0.371	0.393	2013M12	1982M3	3.781	4.272	2013M12	1978M11
Morgantown WV	0.137	0.168	2013M12	1979M10	1.750	2.257	2014M1	1981M1

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Morristown TN	0.658	1.479	1996M9	1982M2	3.922	5.920	2013M12	1980M12
Mount Vernon–Anacortes WA	0.843	1.974	2013M12	1980M12	4.485	6.286	2013M12	1980M12
Muncie IN	0.479	0.817	2002M10	1982M7	3.340	4.367	2005M7	1980M7
Muskegon MI	0.478	0.647	2013M12	1983M12	3.695	5.050	1996M9	2009M5
Myrtle Beach–Conway–North Myrtle Beach SC–NC	0.500	0.866	2013M12	1981M9	3.982	4.888	2013M12	1981M5
Napa CA	0.858	2.046	2013M12	1980M8	3.826	3.678	2004M9	1980M8
Naples–Immokalee–Marco Island FL	0.730	1.393	2013M12	1977M1	3.284	3.788	1988M8	2009M5
Nashville–Davidson–Murfreesboro–Franklin TN	0.776	1.722	1996M9	1980M12	4.465	6.843	2013M12	1981M10
New Bern NC	0.648	1.120	2013M12	1981M3	4.191	5.589	1984M12	1981M3
New Haven–Milford CT	0.202	0.186	2013M10	1980M7	2.777	2.534	2000M10	1983M12
New Orleans–Metairie LA	0.226	0.245	1996M7	1982M12	2.588	2.819	1996M7	2019M10
New York–Newark–Jersey City NY–NJ–PA	0.304	0.471	2007M12	1981M5	3.110	2.927	2014M1	1984M1
Niles–Benton Harbor MI	0.531	0.728	1996M9	1983M12	3.641	5.158	1996M9	1981M5
North Port–Sarasota–Bradenton FL	0.796	1.552	2014M1	1977M1	3.397	4.086	2013M12	2009M5
Norwich–New London CT	0.212	0.212	2014M2	1980M7	2.639	2.391	2018M3	2009M5
Ocala FL	0.820	1.607	2018M3	1977M1	3.802	4.364	2013M11	1977M1
Ocean City NJ	0.230	0.236	2013M12	1979M10	2.882	2.893	2013M8	1980M10
Odessa TX	1.532	3.131	1996M9	1980M11	5.422	8.875	1996M9	1981M9
Ogden–Clearfield UT	0.242	0.273	2013M12	1978M11	2.752	2.760	2013M11	2019M10
Oklahoma City OK	0.173	0.237	2014M1	1978M11	2.315	3.151	2014M1	1979M12
Olympia–Tumwater WA	0.869	2.059	1996M9	1980M8	4.422	6.714	2013M12	1981M1
Omaha–Council Bluffs NE–IA	0.222	0.192	2013M11	2019M5	2.720	3.717	2006M11	1980M2
Orlando–Kissimmee–Sanford FL	0.828	1.643	2013M12	1977M1	3.578	4.192	2013M12	2009M5
Oshkosh–Neenah WI	0.797	1.724	2014M1	1980M10	5.033	8.396	1996M9	1980M7
Owensboro KY	0.317	0.316	1996M9	1979M10	3.348	3.778	2014M1	2019M10
Oxnard–Thousand Oaks–Ventura CA	0.826	1.933	2013M12	1980M8	3.576	3.477	2005M8	1980M8
Palm Bay–Melbourne–Titusville FL	0.786	1.525	2013M12	1977M1	3.700	4.157	2013M11	2009M5
Panama City FL	0.852	1.664	2013M11	1977M1	3.619	4.391	2013M11	2009M5
Parkersburg–Vienna WV	0.145	0.191	2013M12	1979M10	1.741	2.179	2013M12	1981M1
Pensacola–Ferry Pass–Brent FL	0.904	1.780	2014M1	1977M1	3.852	4.732	2013M12	2009M5
Peoria IL	0.621	1.071	1996M9	1984M3	2.503	2.817	1988M8	2019M9
Philadelphia–Camden–Wilmington PA–NJ–DE–MD	0.368	0.395	2013M12	1977M5	3.828	3.564	2013M12	2009M5
Phoenix–Mesa–Scottsdale AZ	0.385	0.698	1996M9	1981M5	3.625	4.647	1996M9	2010M5
Pine Bluff AR	0.195	0.228	2013M12	1977M1	2.347	2.874	2002M5	1977M4
Pittsburgh PA	0.429	0.594	1996M9	1977M4	2.687	3.477	2013M12	1978M11
Pittsfield MA	0.267	0.298	2014M1	1979M12	3.166	2.976	2013M12	1984M1

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Pocatello ID	0.220	0.213	2013M12	2019M4	3.186	3.486	2013M12	2019M10
Port St. Lucie FL	0.765	1.508	2013M12	1977M1	3.460	3.867	2006M10	2009M5
Portland–South Portland ME	0.129	0.152	2007M10	1979M12	2.184	3.049	1996M9	1979M4
Portland–Vancouver–Hillsboro OR–WA	0.414	0.566	2004M9	1980M8	4.710	5.527	2013M12	2009M5
Prescott AZ	0.434	0.794	1996M9	1981M11	3.672	4.595	2005M8	1982M3
Providence–Warwick RI–MA	0.178	0.151	2014M2	1985M4	2.240	1.917	2008M4	2019M10
Provo–Orem UT	0.230	0.256	2004M2	1978M11	2.959	3.230	2014M1	2019M10
Pueblo CO	0.521	0.757	2013M12	1981M3	4.177	4.848	2003M8	2009M5
Punta Gorda FL	0.786	1.526	2013M12	1977M1	3.831	4.281	2013M12	2009M5
Racine WI	0.727	1.574	2013M12	1980M11	5.117	8.038	1996M9	1980M12
Raleigh NC	0.661	1.153	2004M2	1980M12	4.510	5.760	2013M12	2019M9
Rapid City SD	0.154	0.154	2013M10	1981M11	2.591	3.373	2005M7	1981M11
Reading PA	0.372	0.486	1996M9	1977M5	3.270	3.402	2013M12	2019M9
Redding CA	0.921	2.206	1996M9	1980M8	3.900	3.887	1996M9	1980M7
Reno NV	0.132	0.141	1996M9	2006M1	2.793	4.083	1996M9	2009M5
Richmond VA	0.481	0.614	1996M9	1982M10	4.456	5.056	2013M12	2009M5
Riverside–San Bernardino–Ontario CA	0.775	1.791	2013M12	1980M8	3.547	3.532	1996M9	2009M5
Roanoke VA	0.558	0.716	2004M9	1981M5	4.653	5.624	2013M12	2019M9
Rochester MN	0.674	1.422	1996M9	1982M3	3.869	6.350	1996M9	1982M4
Rochester NY	0.571	1.193	1996M7	1982M3	3.318	4.217	2013M10	1984M1
Rockford IL	0.625	1.063	2018M3	1978M12	2.914	3.609	2013M12	2010M5
Rocky Mount NC	0.687	1.206	2013M12	1980M11	4.356	6.241	2004M2	2019M10
Rome GA	0.380	0.358	2013M12	1977M4	2.927	4.297	1996M9	2019M9
Sacramento—Roseville—Arden—Arcade CA	0.834	1.947	1996M9	1980M8	3.874	3.683	2006M9	1980M8
Saginaw MI	0.555	0.710	2013M12	1983M12	3.971	5.433	1996M9	2009M5
Salem OR	0.279	0.249	2004M9	1986M11	4.057	4.571	1977M8	2009M5
Salinas CA	0.779	1.827	2013M12	1980M8	3.612	3.595	2006M10	2009M5
Salisbury MD–DE	0.331	0.373	2015M7	1980M7	2.905	3.362	2013M12	2019M9
Salt Lake City UT	0.245	0.272	2013M12	1978M11	2.924	3.069	2013M12	2019M10
San Angelo TX	1.641	3.343	1996M9	1980M11	5.672	10.485	2014M2	1981M3
San Antonio–New Braunfels TX	1.730	3.471	1996M9	1980M11	5.826	9.717	2014M2	1981M5
San Diego–Carlsbad CA	0.869	2.036	2013M12	1980M8	3.861	3.775	2004M9	2009M5
San Francisco–Oakland–Hayward CA	0.831	1.917	2013M12	1980M8	3.957	3.834	2006M10	2009M5
San Jose–Sunnyvale–Santa Clara CA	0.839	1.945	2013M12	1980M8	3.932	3.709	2014M1	1980M7
San Luis Obispo–Paso Robles–Arroyo Grande CA	0.855	2.029	2013M12	1980M8	3.750	3.671	2016M2	1980M7
Santa Cruz–Watsonville CA	0.869	2.026	2013M12	1980M8	4.038	3.838	1996M9	1980M7
Santa Fe NM	0.183	0.181	2013M12	1979M10	2.235	2.292	2003M8	1980M2
Santa Maria–Santa Barbara CA	0.829	1.931	2013M12	1980M8	3.689	3.597	1984M11	2009M5
Santa Rosa CA	0.833	1.944	2013M12	1980M8	3.929	3.659	2013M12	2009M5

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Savannah GA	0.373	0.323	2013M12	1977M4	3.337	4.774	1996M9	2019M10
Scranton—Wilkes-Barre—Hazleton PA	0.390	0.519	1996M9	1977M5	3.178	3.348	2013M12	2019M10
Seattle–Tacoma–Bellevue WA	0.821	1.931	1996M9	1980M12	4.358	6.174	2013M12	1980M12
Sebastian–Vero Beach FL	0.832	1.662	2013M12	1977M1	3.694	4.330	1988M8	1977M1
Sebring FL	0.806	1.562	2013M12	1977M1	3.869	4.346	2014M1	2009M5
Sheboygan WI	0.736	1.582	2014M1	1980M10	5.046	7.696	1996M9	1980M12
Sherman–Denison TX	1.585	3.202	1996M9	1980M11	5.423	9.329	1996M9	1981M1
Shreveport–Bossier City LA	0.259	0.286	1996M7	1982M11	2.845	3.127	1996M9	2019M9
Sierra Vista–Douglas AZ	0.497	0.935	1996M9	1981M11	3.884	4.875	2013M12	1984M1
Sioux City IA–NE–SD	0.307	0.311	2013M12	1984M1	3.057	3.607	2013M12	2019M10
Sioux Falls SD	0.164	0.151	1996M9	1979M3	2.333	2.576	1996M7	2010M5
South Bend–Mishawaka IN–MI	0.500	0.813	2013M12	1984M1	3.518	4.621	2013M12	1984M1
Spartanburg SC	0.586	1.057	1984M12	1982M7	3.896	6.167	2013M12	1981M11
Spokane–Spokane Valley WA	0.881	2.104	1996M9	1980M11	4.390	6.593	2013M12	1980M11
Springfield IL	0.679	1.212	1990M11	1984M3	2.187	2.646	2013M12	1980M7
Springfield MA	0.290	0.319	2013M12	1978M11	3.058	3.065	2013M12	1984M1
Springfield MO	0.676	1.756	2013M12	1977M1	2.679	3.812	2013M12	1977M4
Springfield OH	0.748	1.417	2013M12	1980M12	4.863	7.334	1996M9	1980M12
St. Cloud MN	0.687	1.412	2013M12	1982M12	3.918	5.875	2013M12	1982M4
St. George UT	0.202	0.225	2014M2	1978M11	2.319	2.540	2014M1	2019M10
St. Joseph MO–KS	0.715	1.849	2013M12	1977M1	2.658	3.873	2013M12	1977M4
St. Louis MO–IL	0.678	1.770	1987M11	1977M1	2.856	4.195	2013M12	1977M4
State College PA	0.427	0.596	2013M12	1977M5	2.822	3.143	2013M12	1980M8
Staunton–Waynesboro VA	0.488	0.611	1996M9	1982M2	4.690	5.462	2013M12	2009M5
Stockton–Lodi CA	0.778	1.804	1996M9	1980M8	3.528	3.574	1984M2	2009M5
Sumter SC	0.605	1.119	2013M12	1981M5	4.164	6.246	2013M12	1984M1
Syracuse NY	0.521	1.074	2007M4	1982M3	3.479	4.072	2013M10	1982M3
Tallahassee FL	0.949	1.874	2014M1	1977M1	3.794	4.704	2014M1	2009M5
Tampa–St. Petersburg–Clearwater FL	0.852	1.679	2014M1	1977M1	3.726	4.316	2013M11	2009M5
Terre Haute IN	0.494	0.838	2013M11	1981M11	3.238	4.331	2013M12	1984M1
Texarkana TX–AR	1.621	3.249	1996M2	1980M11	5.252	8.933	2013M12	1981M5
The Villages FL	0.950	1.894	2015M12	1977M1	3.810	4.561	2013M12	1977M1
Toledo OH	0.771	1.432	2013M12	1980M11	4.675	6.979	1996M9	1980M12
Topeka KS	0.318	0.383	2013M12	1980M1	2.816	4.051	2013M12	2009M5
Trenton NJ	0.243	0.248	2013M10	1980M11	3.040	2.808	2014M1	2009M5
Tucson AZ	0.450	0.826	2013M12	1982M3	3.942	4.963	1995M6	1980M7
Tulsa OK	0.194	0.224	2013M12	1978M11	2.382	3.220	2003M8	1978M11
Tuscaloosa AL	0.378	0.392	2013M11	1982M3	3.650	4.026	2013M12	1979M4
Tyler TX	1.750	3.559	1996M8	1980M11	5.460	9.720	1996M9	1981M9
Urban Honolulu HI	0.255	0.522	2013M12	1980M8	1.875	2.856	2016M5	1979M10

(Continues)

TABLE A.1 (Continued)

MSA	Instantaneous connectedness				Long-run connectedness			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Utica–Rome NY	0.516	1.056	2013M9	1983M4	3.315	3.873	2013M12	1981M11
Valdosta GA	0.378	0.356	2004M2	1977M4	3.162	4.416	2013M12	2010M5
Vallejo–Fairfield CA	0.768	1.763	2013M12	1980M8	3.756	3.833	2006M10	2009M5
Victoria TX	1.834	3.725	1996M9	1980M11	5.733	10.352	1996M9	1980M12
Vineland–Bridgeton NJ	0.275	0.272	2013M11	1979M10	3.166	3.050	2013M12	2019M9
Virginia Beach–Norfolk–Newport News VA–NC	0.426	0.555	1996M9	1983M2	4.159	4.825	2013M12	2009M5
Visalia–Porterville CA	0.852	2.010	2013M12	1980M8	3.701	3.983	2013M12	1980M12
Waco TX	1.723	3.499	1996M9	1980M11	5.559	9.989	1996M7	1981M2
Walla Walla WA	0.881	2.120	1996M9	1980M8	4.379	6.708	2013M12	1981M3
Warner Robins GA	0.469	0.401	2004M3	1977M4	3.332	4.048	2013M12	2019M10
Washington–Arlington–Alexandria DC–VA–MD–WV	0.381	0.464	2013M12	1983M12	3.891	4.377	2014M2	2009M5
Waterloo–Cedar Falls IA	0.264	0.281	2013M12	1984M1	3.268	4.341	2013M11	1978M11
Watertown–Fort Drum NY	0.453	0.903	1996M9	1982M4	3.054	3.135	2013M9	1984M1
Wausau WI	0.830	1.789	2014M1	1980M8	5.022	8.296	2013M12	1980M8
Weirton–Steubenville WV–OH	0.621	1.090	2013M12	1980M8	4.269	6.143	2013M12	1980M12
Wenatchee WA	0.720	1.693	2004M3	1980M8	4.181	6.246	2013M12	1982M2
Wheeling WV–OH	0.432	0.710	2013M12	1980M8	3.386	4.776	2014M1	1981M1
Wichita Falls TX	1.796	3.618	1996M9	1980M11	5.783	9.914	1996M7	1982M2
Wichita KS	0.296	0.345	2007M7	1980M1	2.937	4.023	1988M8	2009M5
Williamsport PA	0.443	0.619	1996M9	1977M5	2.917	3.070	2013M11	2019M9
Wilmington NC	0.584	0.988	2004M2	1980M11	3.902	5.207	1996M2	2019M10
Winchester VA–WV	0.356	0.447	1988M8	1981M7	3.931	4.373	2006M9	2009M4
Winston–Salem NC	0.727	1.268	2013M12	1982M3	4.507	6.353	2004M3	2019M10
Worcester MA–CT	0.273	0.300	2013M12	1978M11	2.949	3.061	2013M12	1984M1
Yakima WA	0.914	2.187	2013M12	1980M8	4.452	7.196	2013M12	1980M12
York–Hanover PA	0.386	0.502	1996M9	1977M5	3.336	3.794	2013M12	2009M5
Youngstown–Warren–Boardman OH–PA	0.726	1.319	1996M9	1980M8	4.777	7.061	2013M12	1980M12
Yuba City CA	0.822	1.934	2013M12	1980M8	3.813	3.672	2013M12	2009M5
Yuma AZ	0.471	0.885	1996M8	1980M11	3.668	4.869	2013M12	2009M5

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