US Housing Prices and the Transmission Mechanism:
A Quantile Connectedness model

Sahana Roy Chowdhury[a*], Kirti Gupta[b] and Panayiotis Tzeremes[c]

[a]International Management Institute, Kolkata, India, [b]Reserve Bank of India, India, [c]University of Thessaly, Greece

Abstract

This research studies the connectedness and spillover possibilities of US house prices in metropolitan areas employing a quantile connectedness model. We use monthly data for the period 2000:01–2023:01 yielded from the S&P/Case–Shiller Home Price Indices and contains 20 metropolitan statistical area**s** (MSAs). We identify the MSAs that could be potential contributors in the house price transmission mechanism either as net contributors or as net receiver. We check these roles of the MSAs across different ranges of prices (quantiles) as well, and interestingly note that for some MSAs the role changes critically, across different price quantiles. To exemplify, Dallas is disclosed to be a tenuous contributor with a strong impactful role during the Covid-19 pandemic at all quantiles levels. After the Covid-19 outbreak, Charlotte displays powerful transmitter impacts at high house prices, the Washington metropolitan area shows stable net-receiving impacts at middle house prices, and a weak transmitter at high house prices until the start of the Covid-19 outbreak, Boston is constantly a receiver of impacts and this phenomenon is intense during the Global Financial Crises. Taking cue from regional interconnectedness of USA house prices, the paper delves deep to provide a 'directional contribution' of house price co-movement across MSAs. The findings provide interesting policy insights in understanding the housing market in USA: house price transmission mechanism and their forecast with better precision. Additionally, the paper finds that West house market regions could be a leading indicator for investment opportunities urging investors to invest in these regions.

JEL Classification: C51, E31, R31

Keywords: House price indices**,** metropolitan statistical area**s**, Quantile Vector Autorergression, global financial crisis, Covid-19

[*] Corresponding author. Contact no.+91 9873835021. Address: International Management Institute Kolkata, 2/4C, Judges Court Road, Alipore, Kolkata 700027, WB, INDIA.
E-mail addresses: sahana.isi@gmail.com (S. Roy Chowdhury), kirtigupta1@rbi.org.in (K. Gupta), tzeremes@uth.gr (P. Tzeremes)

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1. Introduction

Over the pre-GFC (global financial crisis) period during 1996-2006, among a wide variety of economic indicators — house price movements and their large departure from the "warranted level" generated intriguing observations (Shiller, 2007). Ex-post investigations of the GFC show that such a boom in house prices in terms of their magnitude and persistence were unprecedented in the US house price history and they sky-rocketed during Covid-19 pandemic. Lockdowns and increased remote working exponentially escalated the demand for suburban properties (*The Economist*, Oct 2022). While such steep rise in the house prices in select major urban areas may not form a bubble as there are lot more regulations and restrictions in the mortgage market than it was in pre-GFC period; it needs a careful investigation of the fundamentals *viz.,* the long-term interest rates; higher mortgage debt; measures of affordability - median household income, and expected stream of real rents; and the strength of house price transmission or the price-interconnectedness in economically contiguous areas.

The hallmark of house price bubble or any price bubble, is primarily, driven by the belief that the expected price increase closely follows the current price increase. From the reports and surveys of home buyers that are intermittently conducted in the US, there are clinching evidence of both spatial and temporal house-price interlinkages, and their possible connections with an underlying bubble psychology (Rakshit, 2008). Not all the housing areas do significantly contribute to the price interlinkages while some may aggravate, others might dissipate the amplitude of price variations and thereby mitigating formation of bubbles. Prof. Leamer wrote, "The housing cycle is the business cycle", which was empirically tested and found that 10% increase in house prices raises consumption by 0.35–0.5% (Leamer, 2007; BOE, 2019). It is, therefore, pertinent to trace house price co-movements in regions/subregions of the US that are economically contiguous or spatially connected or have had historical evidence of anomalous house price movement behavior. Simultaneously, for more precise and timely policy interventions it is important to examine the strength of such price inter-connectedness at different price ranges (quantiles) as well.

What determines house prices in the US metropolitan areas? While the regulatory atmospheres such as rent control or land use mechanism (Segal and Srinivasan, 1985), economic criteria, fiscal and monetary stimulus (Leamer, 2015) and non-economic or topographic factors (Malpezzi, 1996) play big roles, a more generic concern surrounds possibilities of (and the extent of) a 'mass spill-over effect' of the Metropolitan Statistical Areas (MSAs) bound house price fluctuations beyond that MSA area. House-price linkages between Los Angeles, Las Vegas, and Phoenix and between the eight Southern California metropolitan statistical areas (MSAs) are evidenced in Gupta and Miller (2009, 2012). Canarella *et al*. (2012) considers the "ripple effect", and states that if the ripple effect exists, then a given price shock in a metropolitan area may produce permanent or transitory implications for house prices in other metropolitan areas; Montañés and Olmos (2013) show their convergence possibilities, and confirm the existence of some degree of segmentation in the US housing market. In a more recent study on the lead-lag relationship between US house prices, volume, and their regional dynamic connectedness has been studied by Antonakakis *et al*. (2021). The study pertains to four broad US geographical regions: Midwest, Northeast, South, and West, for the period between January 1990 and March 2019. How either prices or volumes independently co-move across regions was investigated using a time-varying parameter vector autoregressive framework of analysis. The study underscored that integration across different geographical areas has intensified after 2005.

The question becomes more pertinent at a time when house price movements beyond their fundamentals, has been the harbinger of financial crisis in the past.[†] Second, the spill-over effect of house price movements on the real or financial sector are non-negligible (Rünstler and Marente, 2016, Leamer 2007), or rather considerably strong; third, when countries become highly integrated via global trade and financial transactions, the emerging possibilities of a domino effect beyond the politico-economic territories can hardly be ignored. With the evolution of an array of regulatory measures post-GFC, tight macro-prudential norms entailing maintenance of sound bank balance sheet, wild house price movements are less likely to be threatening to financial stability of the US economy. Nevertheless, if the house price movements are in general found to take significant upturn post-pandemic, there are reasons behind a nuanced understanding of inter-regional transmission of the house prices for more precise and timely policy intervention.

Recent data shows that post-pandemic the US house prices spiraled at an annual rate of 13 per cent in Sep 2021, highest in the last 15 years. The accommodative monetary stance (low cost of purchasing) and expansionary fiscal policy have encouraged people to purchase bigger houses. The rising growth in house prices does not seem to pass over to rental prices. Since rental growth is hovering around 2-3 per cent for the last 10 years. In a more recent article, *The Economist* states that mortgage rates are now rising at their fastest pace in decades, and average home prices are rising, and are back on top in America though that still leaves them 12% below their pre-crisis peak [T*he Economist*, May 23rd, 2022] . In Las Vegas, where prices were 70% overvalued compared with incomes in 2005, they now appear about 20% overvalued. [*The Economist*, April 16th, 2021].The Bloomberg (September 8, 2022) highlights that the role of pandemic has not yet been fully recognized, in deepening America's housing affordability crisis, spreading it from superstar cities and tech hubs like New York, Los Angeles and the Bay Area to cities, suburbs and rural areas across the US.

A big strand of the literature in US house price movements as discussed above, provide several empirical and theoretical justifications to underscore possible house price ripple effect, or co-movement and regional inter-connectedness. For example, Tidwell et al. (2023) studies the time-varying nature and determinants of comovements in US housing prices using state and MSA data to estimate the national, regional, and state factors. They find that the national factor is the dominant factor in explaining the movement of housing prices. The insights help in understanding house price bubble formation and its

† *The Economist*, July 18th, 2020: "The housing market has generally been both a reliable predictor of downturns and, frequently, a proximate cause. Serious housing troubles preceded nine of the 11 recessions between the end of the second world war and the start of 2020".

transmission mechanism; however, they do not consider the directional price movements across MSAs or regions. The paper delves deep in an attempt to find the 'directional' contribution in the general US housing price movement in the recent time, and segregate the MSAs from this perspective. The entire dataset covers the period from January, 2000 to January, 2023, using a very recently designed methodology – the Quantile Vector Autoregression (QVAR) Connectedness Model (Ando et al., 2022) (i) to capture the direction of inter-regional transmission of house price movements in the USA by looking primarily, into the direction of the connectedness of the house prices (ii) investigate whether the movements are symmetric or not in different price quantiles and by detecting commonalities between quantiles of the joint distributions of variables across frequencies, in order to identify patterns of correlation between the covariates. (iii) the role of each select metropolitan area as a net transmitter or net recipient of spillover shocks. Our paper adds to the literature on the house price transmission mechanism and price connectedness in prominent US MSAs, and therefore, sheds light on emerging possibilities of any house price contagion in economically contiguous regions. In particular, we further illuminate on some of the challenges of having independent house price regulatory policies – built and implemented in silos, within an increasingly interlinked socio-economic areas. Apart from the fact that it is a very recently designed methodology, one key distinctiveness of the QVAR method as an empirical model is that it has an advantage of taking care of two and several time periods that have had very distinct characteristics, for example, the covid pandemic and GFC.

While we identify MSAs who play big role in spreading this contagion either as net contributors or as net receiver, we also check this role across different price ranges (quantiles), and found that indeed the role changes critically across different price quantiles for some MSAs. The paper underscores that all metropolitan areas do not display the same house price behavior, and different socio-economic factors such as the Covid-19 outbreak play intriguing role in determining the house price movements in the MSAs - net-transmitter, net-receiver or mixed behavior. All the aforementioned evidences provide valuable insights for designing regulatory or other, housing sector policies in the chosen region. In Section 2 we provide the data and methodology, while the empirical results are elaborated in Section 3. We discuss major policy implications emanating from the paper in the last section, and conclude.

2. Data and Methodology

This research studies the connectedness and spillover connection among US house prices by employing a quantile connectedness model. We use monthly data for the period 2000:01–2023:01. The data sample has been yielded from the S&P/Case–Shiller Home Price Indices database and contains 20 MSAs: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington. The time series and returns of the variables are shown in Fig. 1 and 2.

Please Insert Figures 1-2 about here

Concerning the methodological framework, we have used a quantile connectedness model (Chatziantoniou et al., 2021; Ando et al., 2022). A classical QVAR procedure which measures connectedness among the samples can be evaluated as:

$$v_t = o_t(z) + m_1(z)v_{t-1} + m_2(z)v_{t-2} + \cdots + m_q(z)v_{t-q} + w_t(z) \quad (1)$$

in equation (1), a vector of endogenous covariates is depicted by v_t, the quantile of prices is represented by letter z with values $0 - 1$. The lag length of QVAR model is shown by q and a KxK QVAR coefficient matrix is demonstrated with $m_q(z)$. Finally, o_t exhibits a mean vector whilst the error vector is performed with w_t.

Succinctly stated, the total directional connectedness to others (TO) measuring how much of a shock in variable i is transmitted to other could be computed as:

$$TO_i(L) = \sum_{i=1, i \neq j}^{Z} \tilde{g}_{ji}(L) \quad (2)$$

Similarly, the total directional connectedness from others (FROM) measuring how much variable i receives from shocks in other variables could be calculated by:

$$FROM_i(L) = \sum_{i=1, i \neq j}^{Z} \tilde{g}_{ij}(L) \quad (3)$$

Therefore, the net total directional connectedness (NET) can be depicted as:

$$NET_i(L) = TO_i(L) - FROM_i(L) \quad (4)$$

in the above equation, if the outcome of the subtraction is bigger than zero then variable i shows more effect to other covariates j. Hence, we can name that variable as a net transmitter, whilst if the outcome of the subtraction is smaller than zero then variable i is affected more from other covariates j. Thus, we can name that variable as a net receiver. Lastly, we can calculate the degree of network linkage by the total connectedness index (TCI). The TCI measures the average impact of one variable to all others:

$$TCI(L) = Z^{-1} \sum_{i=1}^{Z} TO_i\,(L) = Z^{-1} \sum_{i=1}^{Z} FROM_i\,(L) \quad (5)$$

3. Empirical Results

A first look of a sample is given in Table 1. Specifically, we can notice that Denver shows the smallest variance 0.391 whilst Las Vegas has the largest variance with a value of 2.295. Interesting to observe is that most of the series, employing D'Agostino 1970 test, are left skewed and only three MSAs, Charlotte, Dallas and Denver, are significantly right-skewed. Furthermore, almost all house price variables are significantly non-normally (Jarque-Bera, 1980 normality test), leptokurtic distributed (implementing Anscombe and Glynn, 1983 test), the Fisher and Gallagher (2012) weighted portmanteau test shows that the returns of all the series are significantly autocorrelated, the Stock et al. 1996, (ERS) unit-root test demonstrates that the returns of all the series are stationary. Lastly, the correlation nonlinear test of Kendall is used in order to detect the linkage amongst the variables. Noteworthy is the fact that all prices are positively correlated.

Please Insert Table 1 about here

The estimated outcome of the total dynamic connectedness is calculated via a heatmap graph and illustrated in Figure 3. Specifically, all heatmap graphs were estimated via a 200-days rolling-window QVAR technique with a 20-step-ahead forecast while the lag selection is order 1 using the Bayesian information criterion. Additionally, the left vertical horizon line depicts the quantile distribution (from extreme lower 0.05 to extreme upper 0.95) while the right vertical horizon line shows the degree of TCI (color bar). It is worth mentioning that the larger the degree (warmer shade) of color bar the stronger the TCI of MSAs is, whereas the horizontal axis portrays the years. The findings of the dynamic total connectedness show a strong connectedness at lower house prices (lower quantiles, 0.05^{th} – 0.20^{th}) and at higher house prices (upper quantiles, 0.80^{th} – 0.95^{th}) whilst the total spillover connectedness of median house prices (mean quantiles, 0.40^{th} – 0.60^{th}) appears to be higher after 2017 and towards the end of the period.

Please Insert Figure 3 about here

The estimation outcomes of net directional among MSAs house prices are illustrated in Figures 4-6. When the heatmap color is red (warmer shades), it implies a net-contributing region whereas blue color (colder shades) implies a net-receiving region.

In a nutshell, Denver, Los Angeles, Seattle, Phoenix, San Diego and San Francisco unveil a net-contributing behavior whilst Chicago, Detroit, Las Vegas, Minneapolis, New York and Atlanta show a net-receiving strand. Finally, Portland, Boston, Charlotte, Cleveland, Dallas, Miami, Tampa and Washington denote either a contributing or a receiving role during the time period. Starting our analysis, we can notice that Denver's transmission impacts are detected at lower middle and middle house prices (0.20^{th} – 0.60^{th}), while at the upper- and lower-tail quantiles a weak contribution influence is depicted. Los Angeles is proved to be strongly influential at mean and upper quantiles until 2016 (middle and high house prices), but after this period and towards the end of it, tenuous transmission impacts are revealed. Lastly, we can mention the neutral influence of Los Angeles on low house prices during the entire period. A strong net-contributing role of Seattle is depicted at middle house prices, although this behavior tends to be weak during the Covid-19 outbreak, while at lower quantile (house prices) it renders a weak receiver of impacts. Notable is the neutral role of Seattle at upper middle levels of quantiles. Phoenix shows a net-transmitting role at quantiles across all levels except for the lowest quantiles. It is interesting to mention the powerful transmits impacts of Phoenix at middle house prices after the outbreak of the Global Financial Crisis (2007-2008) until the end of 2016. In the same vein follows San Francisco but this powerful sign exists at the beginning of the period, and it becomes tenuous during the Covid-19 outbreak. Finally, San Diego is clearly a contributor of impacts, this phenomenon is powerful at middle house prices (0.40^{th} – 0.60^{th}). Specifically, it becomes a powerful contributor of influences during the pandemic and more strongly at mean quantile during the Covid-19 outbreak.

Regarding the net receiving MSAs, Chicago and Detroit clearly unveil the same receiving impacts. Both regions are constantly a receiver of impacts whereas they display a strong net-receiving strand at middle house prices (0.40^{th} – 0.60^{th}). Las Vegas exhibits almost the same behavior, albeit not tantamount. It performs a weak receiving influence at mean quantiles between 2010 and 2017. Furthermore, Las Vegas documents a nearly neutral role at the upper- and lower-tail quantiles. A strong receiver impacts is confirmed for Minneapolis at middle quantiles, although this receiver impacts is expanding at upper middle quantiles during the Covid-19 period. Lastly, New York and Atlanta indicate a net-receiving tendency at low middle, middle and upper middle quantiles, even though Atlanta exhibits a neutral period until the beginning of the Covid-19 outbreak.

Concerning the mixed findings, the rest of MSAs denote an idiosyncratic behavior. Portland shows a very weak net-receiving strand at all quantiles, whilst at the lowest quantiles it has an impactful role at the beginning of the sample period, before (subprime market crisis of 2006 that led to the Great Recession) and during the Global Financial Crisis (2007-2008) but during the Covid-19 outbreak we can see the strong net-contributing role of Portland. A double-faced contribution is shown by Cleveland. At low to middle quantiles, it discloses a receiver impacts, whereas at upper middle and upper quantiles it indicates a weak influential behavior. Overall, Dallas is disclosed to be a tenuous contributor with a strong impactful role during the Covid-19 pandemic at all quantiles levels (except for low quantiles), although it starts as a weak net-receiver. Also, a net-receiving behavior at middle house prices is shown for Charlotte, nonetheless, after the Covid-19 outbreak, it displays powerful transmitter impacts at high house prices. The Washington metropolitan area shows stable net-receiving impacts at middle house prices, especially, from 2010 to 2019, and a weak transmitter at high house prices until the start of the Covid-19 outbreak. Almost tantamount is Tampa metropolitan area, a powerful net-receiver at middle quantiles and a weak net-contributor at low quantiles. Miami emerges a strong net-contributing strand at lower middle and middle levels and a neutral orientation at upper middle and upper levels until the year 2015. After that, Miami exhibits a net-receiving aspect at upper middle and upper levels and a neutral role at middle and lower levels. Nonetheless, during the Covid-19 outbreak it shows a powerful receiver impact at all quantiles and especially at lower middle to upper middle house prices. Lastly, Boston is constantly a receiver of impacts at middle house prices and this phenomenon is intense during the Global Financial Crises until the year 2015 and during the Covid-19 pandemic. Also, emphasis should be put on the period of Covid-19 when it becomes a net- contributor at high house prices.

Please Insert Figures 4-6 about here

Taking our findings into account, we can summarize vital evidence. First, all metropolitan areas do not display the same house price behavior. Some MSAs have a net-contributing role (Denver, Los Angeles, Miami, Phoenix, San Diego and San Francisco), others show a net-receiving strand (Chicago, Detroit, Las Vegas, Minneapolis, New York and Portland) and there are those with mixed results (Atlanta, Charlotte, Boston, Cleveland, Dallas, Seattle, Tampa and Washington). It is clear from the above description that almost all Western regions show a net-contributing path and one Southern region (Miami). The latter sign is tandem with Gabauer et al. (2020) and Antonakakis et al. (2021). Moreover, it is interesting to note that New York displays a net-receiving stream from other MSAs, since it has a primary financial strand with an essential section of the foreign residential trade (Holly et al. 2010, 2011; Gabauer et al., 2020 and Antonakakis et al., 2021). Second, a net-transmitter of a shock to other metropolitan areas means that a shock to house prices (positive or negative) will firstly emerge in net-contributing areas and after that it will extend to other metropolitan areas. This is in tandem with a classical phenomenon of house market discipline, called the ripple effect (Meen, 1999; Cook, 2003; Lean and Smyth, 2013). Thus, an increase of house prices in a net-contributing area will extend to other US MSAs. Third crucial evidence is the level of quantiles. As it can be obtained from the results, an idiosyncratic estimation is found in many metropolitan areas which depends on the level of house prices. (i.e. low, middle and high). Finally, different socio-economic factors such as an economic crises or health factors such as the Covid-19 outbreak, play an intriguing role regarding MSAs behavior (net-transmitter, net-receiver or mixed). All the aforementioned evidence could provide new strategies and must be taken into account by policy makers.

4. Conclusion

Investigating and tracing house price movement and co-movement behaviors in the US metropolitan areas have caught specific research attention post-GFC in particular. In this study we focus on the connectedness and spillover possibilities of US house prices employing a quantile connectedness model. We use recent monthly data for the period 2000:01–2023:01, yielded from the S&P/Case–Shiller Home Price Indices database and contains 20 MSAs. Among many interesting results we find that all metropolitan areas do not display the same house price behavior.

We identify the MSAs that could be potential contributors in the house price transmission mechanism either as net contributors or as net receiver. Interestingly, we note that for some MSAs the role changes critically, across different price ranges (quantiles). Moreover, results suggest that total spillover connectedness of median house prices is higher from 2017 to 2022:04 exhibiting the inception of increase in house price before the onset of Covid-19 pandemic. It further suggests the significant role of socio-economic factors in determining house price behavior across MSAs of the US economy. While Covid-19 outbreak has significantly ramped up the house prices across MSAs due to increased remote working and constrained supply. For example, Dallas is disclosed to be a tenuous contributor with a strong impactful role during the Covid-19 pandemic at all quantiles levels (except for low quantiles). After the Covid-19 outbreak, Charlotte displays powerful transmitter impacts at high house prices, the Washington metropolitan area shows stable net-receiving impacts at middle house prices, and a weak transmitter at high house prices until the start of the Covid-19 outbreak, Boston is constantly a receiver of impacts at middle house prices and this phenomenon is intense during the Global Financial Crises until the year 2015 and during the Covid-19 pandemic. Housing price of such MSAs should be constantly gauged and tighter regulation may be maintained.

The findings of the paper provide interesting policy insights: different socio-economic factors, and the Covid-19 outbreak, played crucial role in determining the house price movement behavior in the metropolitan areas of the US economy. Moreover, a net-contributing role of Denver, Los Angeles, Seattle, Phoenix, San Diego and San Francisco could facilitate forecast precision of other USA house price regions. Additionally, West house market regions could be a leading indicator for investment opportunities, which is a news signal urging investors to invest in these regions. Hence, investors/policy makers should give more concentration to this angle and respond appropriately. The paper, however, suffers from some data limitations which is unavoidable at this stage; future extensions of this work may make further refinements.

References

Ando, T., Greenwood-Nimmo, M., & Shin, Y. (2022). Quantile Connectedness: Modeling Tail Behavior in the Topology of Financial Networks. *Management Science*, 68(4): 2377-3174.

Anscombe, F. J., & Glynn, W. J. (1983). Distribution of the kurtosis statistic b 2 for normal samples. *Biometrika*, *70*(1), 227-234.

Antonakakis, N., Chatziantoniou, I. & Gabauer, D. (2021). A regional decomposition of US housing prices and volume: market dynamics and Portfolio diversification. The Annals of Regional Science 66(2), 279–307.

Canarella, G., Miller, S., Pollard, S., (2012). Unit roots and structural change: an application to us house price indices. *Urban Studies* 49 (4), 757–776.

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2021). Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Economics Letters*, *204*, 109891.

Cook, S. (2003). The convergence of regional house prices in the UK. *Urban studies*, *40*(11), 2285-2294.

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika*, 679-681.

Fisher, T. J., & Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*, *107*(498), 777-787.

Gabauer, D., Gupta, R., Marfatia, H., & Miller, S. M. (2020). Estimating U.S. housing price network connectedness: Evidence from dynamic elastic net, lasso, and ridge vector autoregressive models. *Lasso, and Ridge Vector Autoregressive Models (July 26, 2020)*.

Gupta, R., and Miller, S. M., (2009). “Ripple Effects” and Forecasting Home Prices in Los Angeles, Las Vegas, and Phoenix. Working Paper, UNLV.

Gupta, R., Miller, S.M. (2012). The Time-Series Properties of House Prices: A Case Study of the Southern California Market. *Journal of Real Estate Finance and Economics*, 44, 339–361.

Holly, S., Pesaran, M. H., & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, *158*(1), 160-173.

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

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters*, *6*(3), 255-259.

Leamer, EE, (2007). Housing is the business cycle. Technical report, National Bureau Of Economic Research.

Leamer, EE, (2015). Housing really is the business cycle: What survives the lessons of 2008–2009? Journal of Money Credit Bank 47:43–50.

Lean, H. H., & Smyth, R. (2013). Regional house prices and the ripple effect in Malaysia. *Urban Studies*, *50*(5), 895-922.

Malpezzi, S. (1996). Housing Prices, Externalities, and Regulation in U.S. Metropolitan Areas. *Journal of Housing Research*, vol. 7, No. 2, pp. 209-41.

Meen, G. (1999). Regional house prices and the ripple effect: a new interpretation. *Housing studies*, *14*(6), 733-753.

Montañés, A. & Olmos, L., (2013). Convergence in US house prices, *Economics Letters*, 121(2):152-155.

Rakshit, M. (2008). The Subprime Crisis: A Primer. *Money and Finance*, May.

Rünstler, Gerhard & Vlekke, Marente, 2016. "Business, housing and credit cycles," Working Paper Series 1915, European Central Bank.

Segal, D., Srinivasan, P., 1985. The impact of suburban growth restrictions on U.S. housing price inflation, 1975–1978. Urban Geography, 6 (1), 14–26.

Shiller, Robert J. (2007), "Understanding Recent Trends in House Prices and Home Ownership", Paper presented at the Jackson Hole Symposium on Housing, Housing Finance, and Monetary Policy (sponsored by the Federal Reserve Bank of Kansas City), August 31-September 1.

Stock, J., Elliott, G., & Rothenberg, T. (1996). Efficient tests for an autoregressive unit root? *Econometrica*, 64(4), 813–836.

Tidwell, A., Lu, Y., Lee, J. and Banerjee, P. (2023). Nature of comovements in US state and MSA housing prices. *Real Estate Economics*.

Table 1 Descriptive statistics and pretests.

	Atlanta	Boston	Charlotte	Chicago	Cleveland	Dallas	Denver	Detroit	LasVegas	LosAngeles
Mean	0.296	0.398	0.332	0.220	0.194	0.375	0.403	0.188	0.360	0.491
Variance	1.475	0.481	0.665	0.603	0.490	0.892	0.419	1.057	2.471	1.313
Skewness	-0.890***	-0.168	0.055	-0.866***	-0.752***	0.252*	0.050	-0.839***	-0.443***	-0.921***
Kurtosis	4.868***	-0.018	0.912**	1.853***	5.309***	1.666***	1.246***	2.262***	2.694***	1.546***
JB	308.903***	1.307	9.713***	73.999***	350.155***	34.846***	17.968***	91.241***	92.491***	66.478***
ERS	-6.042***	-2.666***	-5.331***	-2.834***	-4.134***	-3.060***	-2.813***	-2.737***	-3.308***	-2.947***
Q(20)	420.638***	574.063***	432.768***	642.140***	216.318***	420.616***	615.065***	758.283***	1114.622***	1224.430***
Q2(20)	227.267***	225.612***	384.025***	156.767***	78.682***	336.396***	519.373***	329.125***	467.100***	659.173***
kendall	Atlanta	Boston	Charlotte	Chicago	Cleveland	Dallas	Denver	Detroit	LasVegas	LosAngeles
Atlanta	1.000***	0.293***	0.592***	0.283***	0.233***	0.608***	0.301***	0.288***	0.434***	0.260***
Boston	0.293***	1.000***	0.216***	0.510***	0.381***	0.245***	0.449***	0.414***	0.377***	0.452***
Charlotte	0.592***	0.216***	1.000***	0.254***	0.224***	0.583***	0.244***	0.227***	0.354***	0.197***
Chicago	0.283***	0.510***	0.254***	1.000***	0.350***	0.183***	0.366***	0.444***	0.414***	0.514***
Cleveland	0.233***	0.381***	0.224***	0.350***	1.000***	0.211***	0.366***	0.332***	0.323***	0.320***
Dallas	0.608***	0.245***	0.583***	0.183***	0.211***	1.000***	0.338***	0.224***	0.323***	0.154***
Denver	0.301***	0.449***	0.244***	0.366***	0.366***	0.338***	1.000***	0.448***	0.341***	0.365***
Detroit	0.288***	0.414***	0.227***	0.444***	0.332***	0.224***	0.448***	1.000***	0.386***	0.413***
LasVegas	0.434***	0.377***	0.354***	0.414***	0.323***	0.323***	0.341***	0.386***	1.000***	0.548***
LosAngeles	0.260***	0.452***	0.197***	0.514***	0.320***	0.154***	0.365***	0.413***	0.548***	1.000***
Miami	0.387***	0.429***	0.331***	0.555***	0.285***	0.286***	0.308***	0.337***	0.521***	0.570***
Minneapolis	0.277***	0.493***	0.207***	0.497***	0.333***	0.202***	0.391***	0.477***	0.346***	0.481***
NewYork	0.274***	0.514***	0.228***	0.565***	0.328***	0.184***	0.329***	0.338***	0.474***	0.581***
Phoenix	0.448***	0.345***	0.393***	0.399***	0.313***	0.345***	0.353***	0.375***	0.554***	0.499***
Portland	0.275***	0.312***	0.309***	0.448***	0.313***	0.266***	0.407***	0.372***	0.431***	0.476***
SanDiego	0.237***	0.526***	0.170***	0.480***	0.366***	0.178***	0.425***	0.404***	0.476***	0.674***
SanFransisco	0.255***	0.467***	0.191***	0.449***	0.335***	0.205***	0.497***	0.411***	0.415***	0.568***

Seattle	0.526***	0.232***	0.517***	0.301***	0.182***	0.510***	0.269***	0.237***	0.428***	0.302***
Tampa	0.309***	0.428***	0.275***	0.550***	0.359***	0.244***	0.423***	0.364***	0.515***	0.567***
Washington	0.227***	0.493***	0.160***	0.502***	0.313***	0.157***	0.311***	0.349***	0.423***	0.630***

	Miami	Minneapolis	NewYork	Phoenix	Portland	SanDiego	SanFransisco	Seattle	Tampa	Washington
Mean	0.501	0.298	0.359	0.407	0.417	0.485	0.433	0.450	0.471	0.394
Variance	1.725	0.892	0.501	2.399	0.651	1.425	1.900	1.611	1.308	0.775
Skewness	-1.104***	-1.694***	-0.219	-0.851***	-0.610***	-0.586***	-0.875***	-0.121	-0.540***	-0.554***
Kurtosis	2.032***	5.263***	-0.208	2.532***	0.562*	0.819**	1.241***	1.910***	0.869**	0.595*
JB	103.592***	450.530***	2.699	107.014***	20.734***	23.499***	52.930***	42.637***	22.106***	18.218***
ERS	-2.459**	-3.336***	-2.351**	-3.400***	-2.503**	-2.499**	-1.880*	-6.327***	-2.529**	-2.635***
Q(20)	1266.742***	498.129***	1119.203***	1048.466***	877.512***	1062.545***	698.153***	436.118***	1228.492***	1165.898***
Q2(20)	589.168***	146.631***	463.978***	623.011***	386.303***	537.498***	450.696***	174.291***	579.480***	793.616***

kendall	Miami	Minneapolis	NewYork	Phoenix	Portland	SanDiego	SanFransisco	Seattle	Tampa	Washington
Atlanta	0.387***	0.277***	0.274***	0.448***	0.275***	0.237***	0.255***	0.526***	0.309***	0.227***
Boston	0.429***	0.493***	0.514***	0.345***	0.312***	0.526***	0.467***	0.232***	0.428***	0.493***
Charlotte	0.331***	0.207***	0.228***	0.393***	0.309***	0.170***	0.191***	0.517***	0.275***	0.160***
Chicago	0.555***	0.497***	0.565***	0.399***	0.448***	0.480***	0.449***	0.301***	0.550***	0.502***
Cleveland	0.285***	0.333***	0.328***	0.313***	0.313***	0.366***	0.335***	0.182***	0.359***	0.313***
Dallas	0.286***	0.202***	0.184***	0.345***	0.266***	0.178***	0.205***	0.510***	0.244***	0.157***
Denver	0.308***	0.391***	0.329***	0.353***	0.407***	0.425***	0.497***	0.269***	0.423***	0.311***
Detroit	0.337***	0.477***	0.338***	0.375***	0.372***	0.404***	0.411***	0.237***	0.364***	0.349***
LasVegas	0.521***	0.346***	0.474***	0.554***	0.431***	0.476***	0.415***	0.428***	0.515***	0.423***
LosAngeles	0.570***	0.481***	0.581***	0.499***	0.476***	0.674***	0.568***	0.302***	0.567***	0.630***
Miami	1.000***	0.444***	0.573***	0.542***	0.422***	0.477***	0.419***	0.397***	0.622***	0.553***
Minneapolis	0.444***	1.000***	0.467***	0.388***	0.312***	0.509***	0.454***	0.245***	0.390***	0.484***
NewYork	0.573***	0.467***	1.000***	0.405***	0.406***	0.530***	0.427***	0.303***	0.569***	0.597***
Phoenix	0.542***	0.388***	0.405***	1.000***	0.460***	0.436***	0.457***	0.449***	0.492***	0.450***
Portland	0.422***	0.312***	0.406***	0.460***	1.000***	0.391***	0.443***	0.419***	0.526***	0.369***
SanDiego	0.477***	0.509***	0.530***	0.436***	0.391***	1.000***	0.598***	0.249***	0.475***	0.584***

SanFransisco	0.419***	0.454***	0.427***	0.457***	0.443***	0.598***	1.000***	0.281***	0.481***	0.501***
Seattle	0.397***	0.245***	0.303***	0.449***	0.419***	0.249***	0.281***	1.000***	0.332***	0.279***
Tampa	0.622***	0.390***	0.569***	0.492***	0.526***	0.475***	0.481***	0.332***	1.000***	0.509***
Washington	0.553***	0.484***	0.597***	0.450***	0.369***	0.584***	0.501***	0.279***	0.509***	1.000***

Notes: ***, ** and * exhibit significance at 1%, 5% and 10%.

Figure 1 Time series plot of the variables.

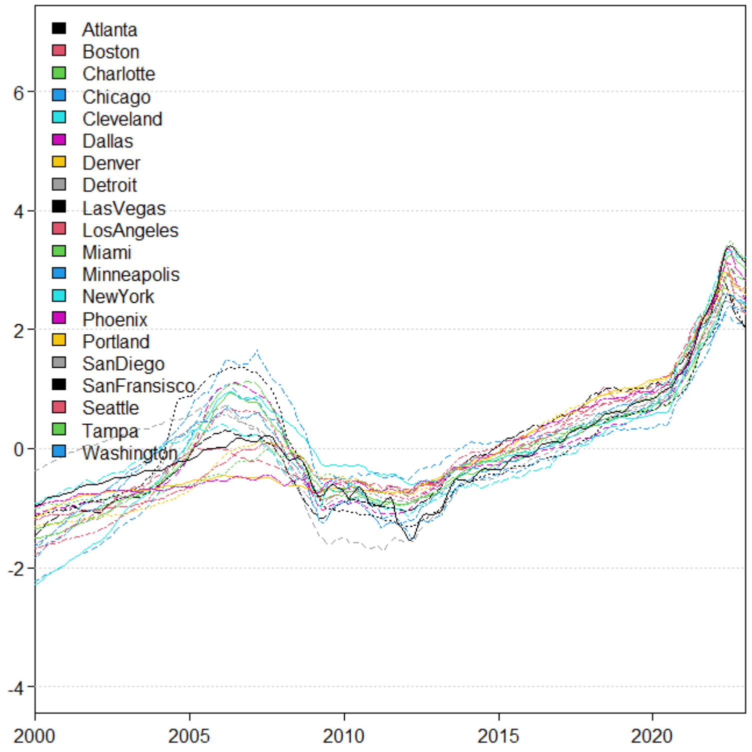


Figure 2 Returns plot of the variables.

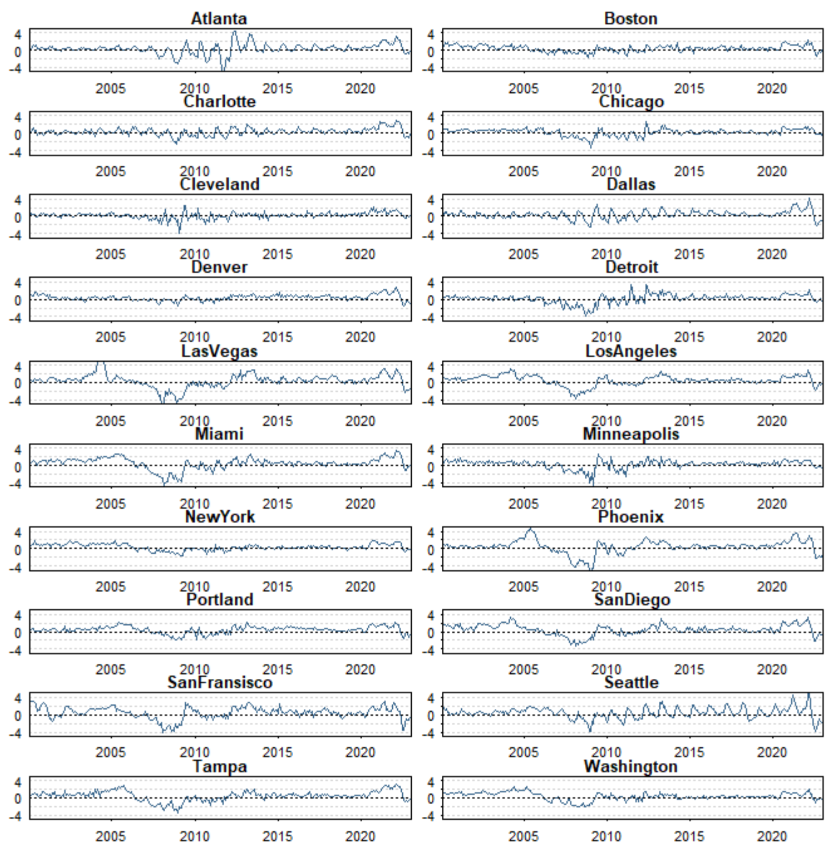
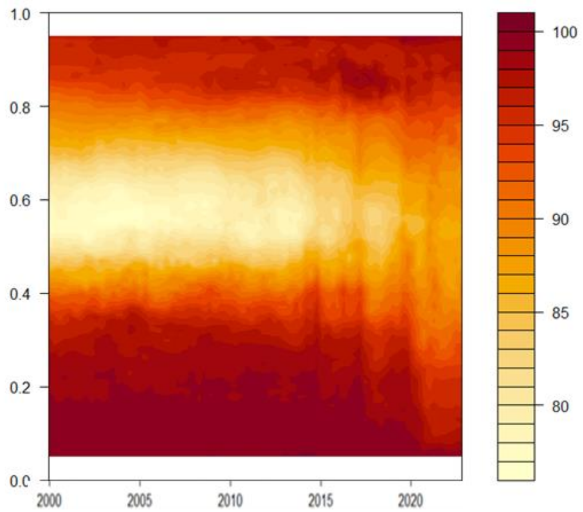
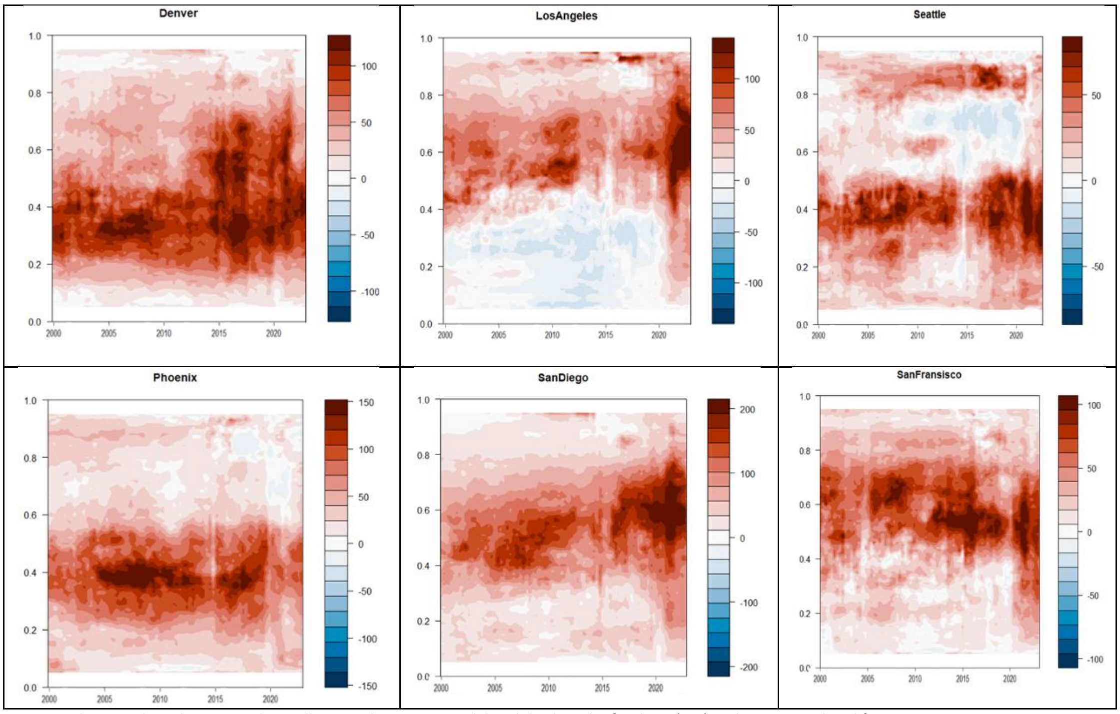


Figure 3 Dynamic total connectedness.



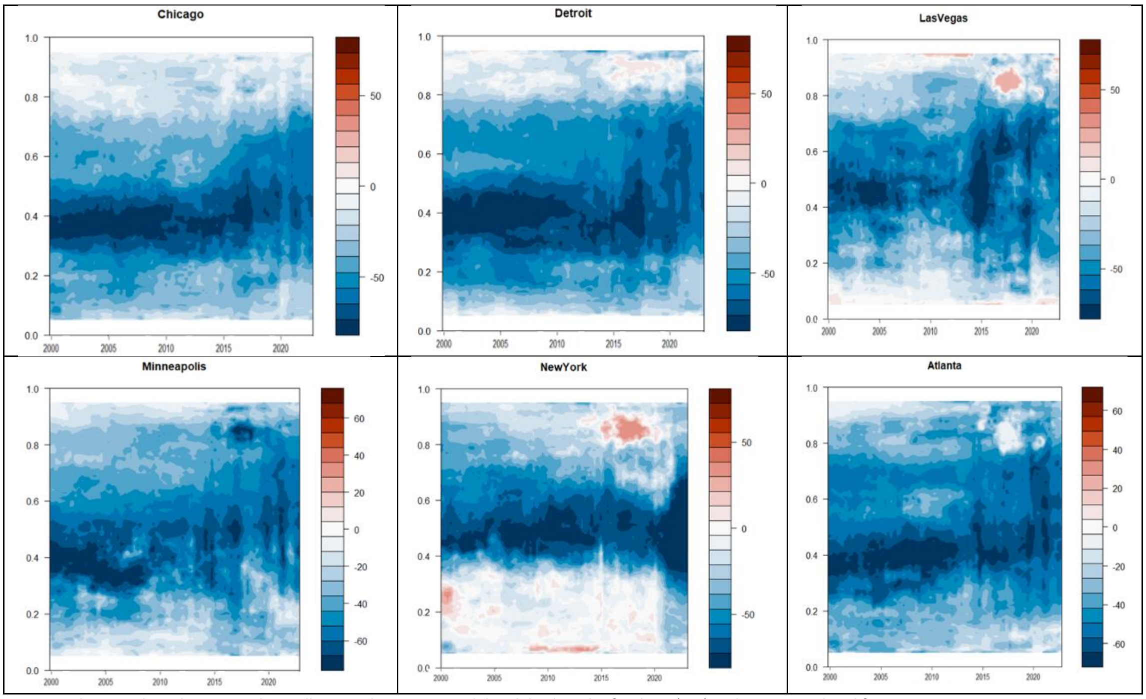
Notes: Findings are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast.

Figure 4 Net total directional connectedness of net-contributing MSAs.



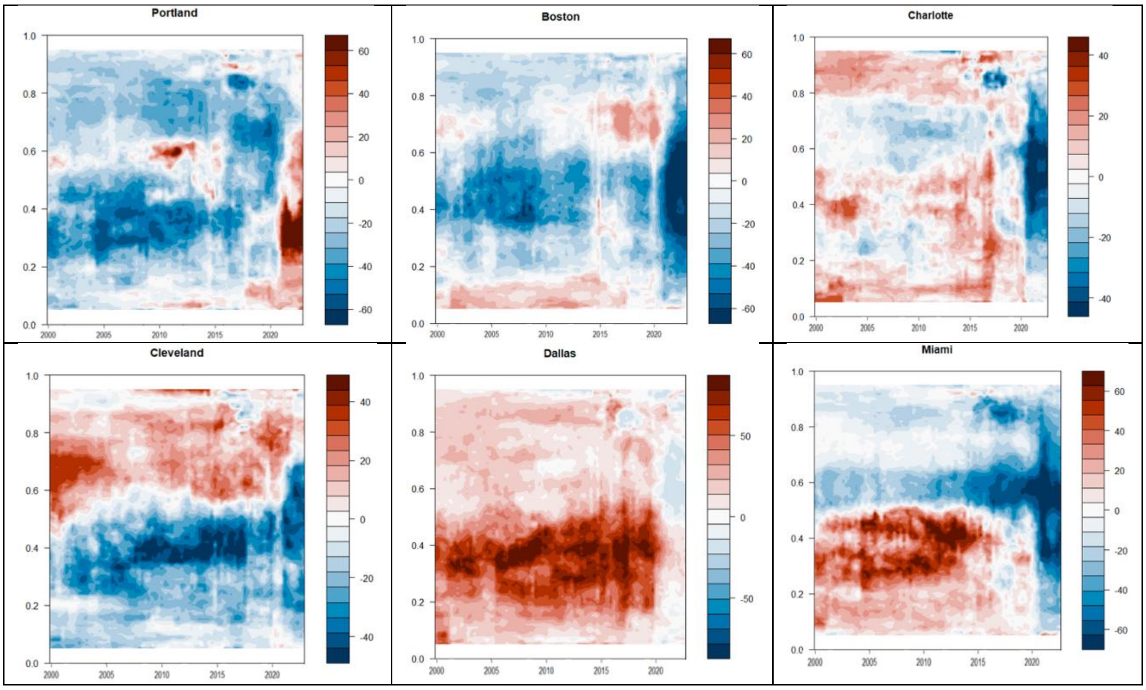
Notes: Findings are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast.

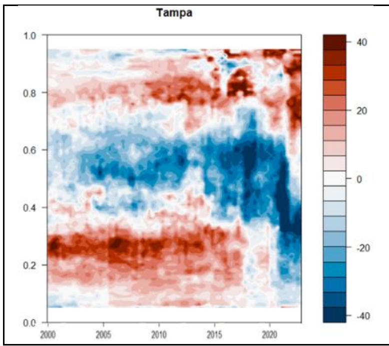
Figure 5 Net total directional connectedness of net-receiving MSAs.

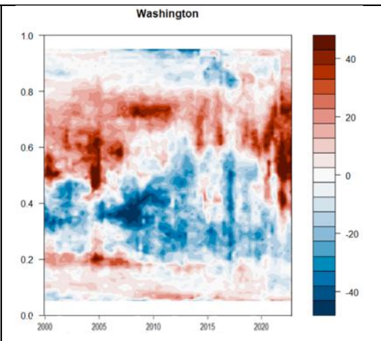


Notes: Findings are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast.

Figure 6 Net total directional connectedness of mixed findings.







Notes: Findings are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast.