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Spillovers across macroeconomic, financial and real estate uncertainties: A time-varying approach☆

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ABSTRACT

We investigate the spillover across real estate (REU), macroeconomic (MU) and financial uncertainties (FU) in the United States based on monthly data covering the period of July, 1970 to December, 2017. To estimate the propagation of uncertainties across the sectors, a time-varying parameter vector autoregression (TVP-VAR)-based connectedness procedure has been applied. In sum, we show that that since the 1970s, FU has been the main transmitter of shocks driving both, MU and REU, with MU dominating the REU. Our results support the need for better macroprudential policy decisions.

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1. Introduction

Following the 'Great Recession' a burgeoning literature has aimed to develop time-varying measures of economic uncertainty (risk), and quantify its impact on the macroeconomy and financial markets (Gupta et al., 2018). In this regard, while studies like Jurado et al. (2015), Baker et al. (2016) and Rossi and Sekhposyan (2015) develop measures of macroeconomic and financial uncertainties, Nguyen Thanh et al. (2018) obtained time-varying estimates of uncertainty associated with the US real estate sector, considered as a leading indicator for US business cycles (Leamer, 2015).

Against this backdrop, the objective of our paper is to utilize the connectedness approach of Diebold and Yılmaz (2009, 2012, 2014), but based on a fully-fledged time-varying parameter vector autoregression with heteroscedastic volatility (TVP-VAR), as suggested by Antonakakis and Gabauer (2017) and Korobilis and Yilmaz (2018), to analyse the spillovers across the measures of macroeconomic, financial and real estate uncertainties. The TVP-VAR framework improves the widely-used above-mentioned traditional methodology of spillovers analysis substantially, since we do not need to arbitrarily set the size of the rolling-window and hence, there is no loss of observations. In addition, the results are not sensitive to outliers as the approach is build on multivariate Kalman filters (Durbin and Koopman, 2012). Given the historical interconnectedness across the real, financial and housing sectors of the US economy (Emirmahmutoglu et al., 2016; Li et al., 2015), this analysis of time-variation in spillover of corresponding uncertainties is, understandably, of paramount importance to policy authorities. This is because, if indeed these measures are connected, then uncertainty of a particular sector can end up increasing even when the shock did not originate in that sector. In addition, the effects of the uncertainty shocks are likely to be prolonged via the feedbacks across the measures of sectoral uncertainties. In sum, interrelatedness is likely to deepen the well-established negative impacts of uncertainty shocks (Bloom, 2009) on the economy as a whole. Given that, we analyse time-varying spillover of sectoral uncertainties, and hence can determine which uncertainty is actually the driver of overall uncertainty, policymakers can use the information to decide on sector-specific policies to ensure against the recessionary impact of heightened uncertainty.

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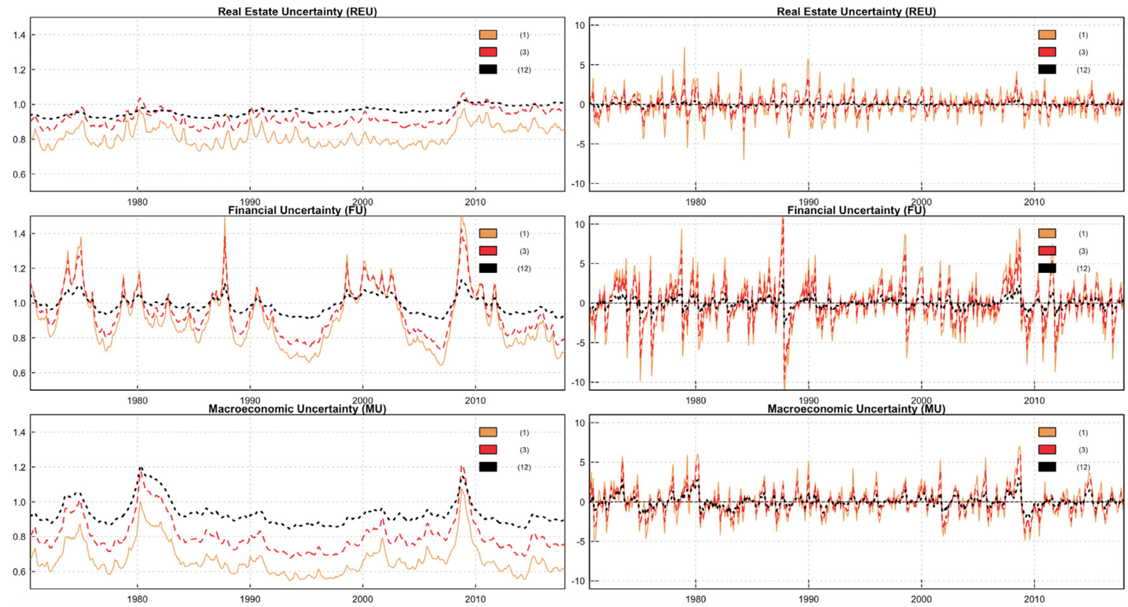

Fig. 1. Raw & first log-differenced series.

Table 1
Summary statistics.

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	$Q(12)$	$Q^2(12)$	Obs.
REU(1)	0.013	0.073	7.197	−6.967	1.603	0.080	4.480***	52.5***	340.7***	62.7***	569
FU(1)	−0.078	−0.107	14.634	−13.442	3.144	0.029	4.673***	66.5***	240.3***	453.5***	569
MU(1)	−0.015	−0.120	7.023	−4.888	1.915	0.438***	3.908***	37.8***	303.9***	223.6***	569
REU(3)	0.012	−0.011	3.505	−3.333	0.919	0.167	3.979***	25.4***	400.5***	100.8***	569
FU(3)	−0.060	−0.082	10.466	−9.658	2.299	0.025	4.552***	57.1***	269.6***	488.0***	569
MU(3)	−0.013	−0.074	5.930	−3.945	1.454	0.613***	4.691***	103.5***	482.9***	418.0***	569
REU(12)	0.013	0.006	0.783	−0.597	0.201	0.389***	3.566 **	21.9***	587.5***	303.0***	569
FU(12)	−0.021	−0.025	2.915	−2.750	0.685	0.026	4.300***	40.1***	379.0***	599.1***	569
MU(12)	−0.005	−0.052	2.996	−1.917	0.732	0.691***	4.876***	128.7***	760.9***	674.9***	569

Notes: ***,**,* denote significance level at 1%, 5% and 10%; Skewness: D'Agostino (1970)test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; $Q(12)$ and $Q^2(12)$: Fisher and Gallagher (2012) weighted portmanteau test.

While, there exists quite a few studies that have analysed the spillover of uncertainty across international economies (see for example, Ajmi et al., 2014; Antonakakis et al., 2018; Balli et al., 2017; Cekin et al., 2019; Colombo, 2013; Gabauer and Gupta, 2018; Gupta et al., 2019; 2016; Klößner and Sekkel, 2014; Yin and Han, 2014), to the best of our knowledge this is the first attempt to study the connectedness across the uncertainties associated with the macroeconomy, financial and real estate markets of the US economy.[1]

The remainder of this study is organised as follows: Section 2 presents information with regard to the employed data and Section 3 outlines the empirical methods. Then, Section 4 proceeds with the exposition and interpretation of the relevant findings. Section 5 concludes the study.

2. Data

Our data set covers the monthly period of 1970:07 to 2017:12, with the start and end date being purely driven by the availability of the real estate uncertainty (REU) index developed by Nguyen Thanh et al. (2018), whose methodological framework for the construction of the REU measure follows that of Jurado et al. (2015). Specifically speaking, the macroeconomic uncertainty (MU) and financial uncertainty (FU) measures of Jurado et al. (2015) and Ludvigson et al. (2015), is the average time-varying variance in the unpredictable component of 134 macroeconomic and 148 financial time-series respectively, i.e., it attempts to capture the average volatility in the shocks to the factors that summarize real and financial conditions.[2] Given this, Nguyen Thanh et al. (2018) link uncertainty directly to the predictability of 40 housing market variables.[3] The various uncertainty indices are available for three forecasting horizons of one-, three-, and twelve-month-ahead, which in turn enables us to analyze short, medium- and long-term spillovers across the sectoral uncertainty indices. In Table A.1, we see that all series in their level form are non-stationary for at least one stationarity or unit-root test. Hence, we apply the first log-differenced series for our analysis which can be interpreted as the monthly percentage changes. The raw and transformed series are illustrated in Fig. 1.

Table 1 shows the summary statistics of the first-log differenced series which indicate that all series are significantly non-normally distributed (Jarque and Bera, 1980) and stationary on at 1%

[1] Two studies that are somewhat related to our work is that of Ajmi et al. (2015) and Liow et al. (2018). Both these studies use rolling-window approaches, with the first one analysing causal relationship between equity and macroeconomic uncertainties of the US, while the latter dealt with international spillover of uncertainty and financial stress.

[2] The MU and FU indices are available for download from: www.sydneyludvigson.com/data-and-appendixes.

[3] The REU index is downloadable from: sites.google.com/site/johannespstrobel/.

significance level. In addition, we find strong evidence for autocorrelation in the series and squared series (Fisher and Gallagher, 2012) implying that the first two moments are varying over time. This supports the choice of estimating a TVP-VAR model with a time-varying variance-covariance structure.

3. Methodology

A widely used approach to trace and evaluate spillovers in a predetermined network is the connectedness approach proposed by Diebold and Yılmaz (2009, 2012, 2014). In the seminal papers the dynamics are estimated via a rolling-window VAR approach which faces some drawbacks such as (i) outlier sensitivity, (ii) arbitrarily chosen rolling-window sizes, (iii) loss of observatsions and (iv) the inability to analyze low-frequency datasets. Emloying a TVP-VAR based connectedness framework – which is used in this study – overcomes those shortcomings as it is intensively discussed in Antonakakis and Gabauer (2017) and Korobilis and Yilmaz (2018). Hence, this study applies the same methodology as in Antonakakis et al. (2018) and Gabauer and Gupta (2018). In particular, we are estimating the following TVP-VAR(1) model as suggested by the Bayesian information criterion (BIC)[4] which can be outlined as follows,

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \quad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \quad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t), \tag{2}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vector and $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $k^2 \times 1$ dimensional vectors whereas $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix.

In a further step, we are calculating the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998). Notably, the GFEVD is completely invariant of the variable ordering opposed to the orthorgonalized forecast error variance decomposition (see, Diebold and Yılmaz, 2009).[5] Since this concept requires to transform the TVP-VAR into a TVP-VMA model we make use of the Wold representation theorem: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$.

The (scaled) GFEVD ($\tilde{\phi}_{ij,t}^{g}(H)$) normalizes the (unscaled) GFEVD ($\phi_{ij,t}^{g}(H)$) in order that each row sums up to unity. $\tilde{\phi}_{ij,t}^{g}(H)$ represents the influence variable j has on variable i in terms of its forecast error variance share which is defined as the *pairwise directional connectedness from j to i*. This indicator is computed by,

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i' \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}_t' \boldsymbol{\iota}_i)} \qquad \tilde{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij,t}^{g}(H)},$$

with $\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = k$, and $\boldsymbol{\iota}_j$ corresponds to a selection vector with unity on the jth position and zero otherwise.

Based upon the GFEVD, Diebold and Yılmaz (2012, 2014) derived their connectedness measures which are mathematically formulated as follows:

$$TO_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{3}$$

$$FROM_{jt} = \sum_{j=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{4}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{5}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{6}$$

$$NPDC_{ji,t} = \tilde{\phi}_{ji,t}(H) - \tilde{\phi}_{ij,t}(H). \tag{7}$$

As mentioned previously $\tilde{\phi}_{ij,t}^{g}(H)$ illustrates the impact a shock in variable j has on variable i. Hence, Eq. (3) represents the aggregated impact a shock in variable j has on all *other* variables which is defined as the *total directional connectedness to others* whereas Eq. (4) illustrates the aggregated influence all *other* variables have on variable j that is defined as the *total directional connectedness from others*.

Eq. (5) : Subtracting the impact variable j has on others by the influence *others* have on variable j results in the *net total directional connectedness* which provides us with information whether a variable is a net transmitter or a net receiver of shocks. Variable j is a net transmitter (*receiver*) of shocks – and hence driving (*driven by*) the network – when the impact variable j has on others is larger (*smaller*) than the influence all others have on variable j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Another essential measure is given by Eq. (6) which represents the *total connectedness index (TCI_t)* that is the average impact one variable has on all *others*. If this measure is relatively high it implies that the interconnectedness of the network and hence the market risk is high and vice versa. Since all aforementioned measures offer information on an aggregated basis, Eq. (7) tells us more about the bilateral relationship between variable j and i. The so-called *net pairwise directional connectedness ($NPDC_{ij,t}$)* exhibits whether variable i is driving or driben by variable j. Therefore, we subtract the impact variable i has on variable j from the influence variable j has on variable i. If $NPDC_{ji,t} > 0$ ($NPDC_{ji,t} < 0$), it means that variable j is dominating (dominated by) variable i.

4. Empirical results and discussion

4.1. Average and dynamic total connectedness measures

We begin our analysis by presenting averaged connectedness measures. Results are provided in Table 2. It should be noted that the main diagonal of Table 2 reflects responses to lagged shocks in the same variable, while, off-diagonal elements represent the interaction across the bases of the various uncertainty indices. More particularly, FU and MU seem to be the primary transmitters of shocks whereas the receiver of shocks within the network is REU.[6] In more detail, we find that 24.48% [34.20%] {42.37%} of REU's

[4] Throughout this study, we base the number of lags on the BIC (Schwarz et al., 1978) as it selects more parsimonious models than alternatives, such as AIC (Akaike, 1969), AICc (Hsiao et al., 2012), HQ (Hannan and Quinn, 1979; Quinn, 1980) and FPE (Akaike, 1970) which in turn leads to better inferences in a TVP-VAR setup, as the model can get overparameterized very quickly, especially when using low frequency, i.e., monthly (as in our case) or quarterly data, rather than daily data (Antonakakis and Gabauer, 2017; Korobilis and Yilmaz, 2018).

[5] We want to stress out that even though we are talking about the spillovers of shocks we are well aware that those interpretation differs from the macroeconomic literature, however, with this interpretation we are just following the interpretations Diebold and Yılmaz (2009, 2012, 2014) to be in-line with the connectedness literature.

[6] Using a narrower measure of macroeconomic uncertainty, i.e., real uncertainty (RU) obtained from 73 variables related to real activity, also developed by Ludvigson et al. (2015), not surprisingly, the dominance of FU continues to hold as shown in Table A.2 in the Appendix of the paper. But now, REU dominates RU, providing some evidence of a leading indicator role of real estate for the real sector of the economy.

Table 2
Averaged dynamic connectedness measures.

	REU(1)[3]{12}	FU(1)[3]{12}	MU(1)[3]{12}	FROM others
REU(1)[3]{12}	75.52 [65.80] {57.63}	6.65 [11.59] {18.92}	17.83 [22.61] {23.45}	24.48 [34.20] {42.37}
FU(1)[3]{12}	1.46 [3.92] {10.39}	88.39 [82.20] {75.92}	10.16 [13.88] {13.69}	11.61 [17.80] {24.08}
MU(1)[3]{12}	11.39 [13.98] {16.00}	13.62 [17.71] {19.95}	75.00 [68.31] {64.05}	25.00 [31.69] {35.95}
TO Others	12.85 [17.90] {26.39}	20.26 [29.29] {38.87}	27.99 [36.49] {37.14}	61.10 [83.69] {102.40}
NET	−11.63 [−16.30] {−15.97}	8.65 [11.50] {14.79}	2.98 [4.80] {1.19}	TCI
NPDC	0 [0] {0}	2 [2] {2}	1 [1] {1}	20.37 [27.90] {34.13}

Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 12-step-ahead forecast.

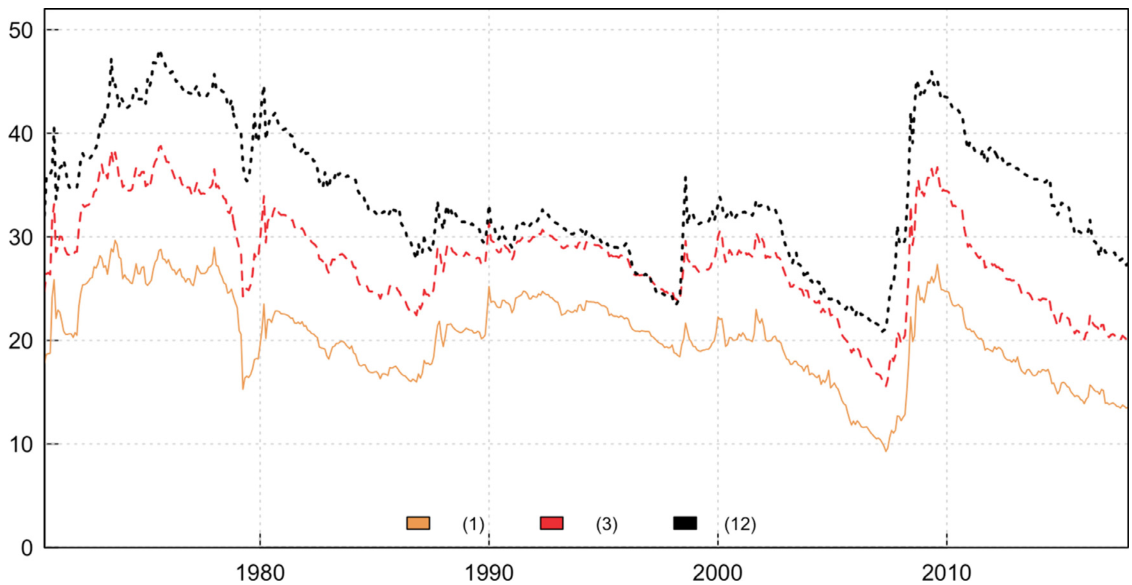

Fig. 2. Dynamic total connectedness. *Notes:* Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 12-step-ahead forecast.

forecast error variance can be explained by FU and MU whereas REU just account for 12.85% [17.90%] {26.39%} of the forecast error variance of FU and MU. Thus, FU and MU explain 11.63% [16.30%] {15.97%} more of the forecast error variance of REU than vice versa. These results are in-line with what could be expected and are stable across different uncertainty horizons which further supports the demonstrated results.

Furthermore, the TCI values are indicative of the fact that comovements within this particular system of variables are rather moderate, as they constitute at least 20.37% of every variables' forecast error variance on average. The cross-variable influence increases with the uncertainty horizon and reaches at max 34.13%. Hence, this network seems to be considerably interconnected which could lead to substantial uncertainty transmission mechanisms across variables.

However, results reported in Table 2 are aggregate results that consider the period of study in its entirety; that is, without emphasizing specific economic or political events that may have resulted in considerable deviations from the average TCI value which is reported above. In this regard, to identify specific episodes that affected connectedness across bases over time, we proceed with the dynamic approach. The results are illustrated in Fig. 2.

Interestingly enough, we note that the dynamic connectedness of our network fluctuates considerably over time, which is suggestive of the fact that connectedness across uncertainties are time-dependent. A closer look at Fig. 2 reveals that pronounced connectedness is evident during the 1970s caused by the US energy crisis which has significantly influenced the US economy as oil is one of the major production inputs. Another peak can be observed in 1980 when the US economy suffered from the early 1980s recession. Finally, the largest increase in the TCI can be associated with the Global Financial Crisis in 2008 triggered by the Lehman Brothers bankruptcy.

4.2. Net pairwise & net total directional connectedness

In turn, we focus on the net total and net pairwise directional connectedness measures of the system which is presented in Fig. 3. Net total connectedness practically shows the difference between the receiving and the transmitting end of each uncertainty index considering the entire network. Since the net total directional connectedness measures may mask essential bilateral relationships we discover them by the net pairwise directional connectedness measures.

We see that the REU have been a net receiver throughout the period of analysis. If we split it up into the net pairwise directional connectedness measures with respect to FU and MU, we see that both uncertainty measures dominated the REU nearly throughout the whole period. In case of FU, we observe that it has been a net transmitter of shocks during the whole sample size with exception of the long-term FU which has been a receiver of shocks in the 1970s. Looking at the disaggregated measures make us realize that the negative impact has been coming from the FU to MU relationship which could be associated with the energy crisis that strongly affected the financial market through the US macroeconomy. More generally, we observe that MU accounts for 10.16% [13.88%] {13.69%} of the FU's forecast error variance whereas FU explains 13.62% [17.71%] {19.95%} of MU's forecast

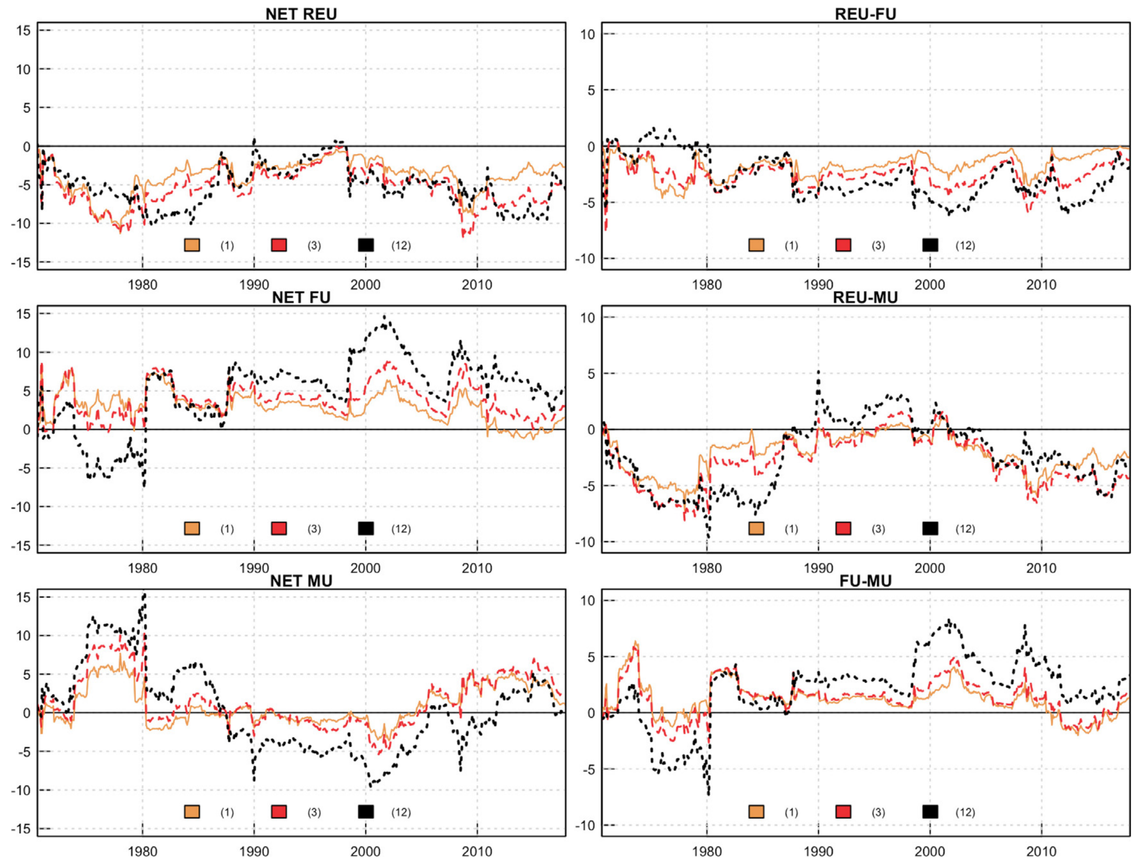

Fig. 3. Net total & pairwise directional connectedness. *Notes:* Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 12-step-ahead forecast.

error variance. Consequently, FU dominates MU as it explains 3.46% [3.83%] {6.26%} more which in turn qualifies FU to be the main net pairwise transmitter of shocks.

Besides this discrepancy, all other findings coincide with each other and show that the FU is nearly permanently dominating the REU and MU.[7] Finally, the MU switches from its behavior between being a net transmitter or net receiver multiple times. Closely observing the pairwise spillovers let us realize that the MU nearly constantly dominates the REU whereas the MU is dominated by the FU as previously mentioned.

5. Concluding remarks

This study investigates the spillover across financial, macroeconomic, and real estate uncertainties over the monthly period of July, 1970 to December, 2017. In this regard, we use a time-varying parameter vector autoregression (TVP-VAR)-based connectedness procedure. Overall, we show that, since the 1970s the financial uncertainty has been the main transmitter of shocks driving both, macroeconomic and real estate uncertainties, with macroeconomic uncertainty in general dominating the real estate uncertainty. These results have important portfolio and risk management as well as policy implications, as it reveals that the uncertainy in the real estate market is driven by the financial sector and the macroeconomy in general.

Our results tend to suggest that the spillover of a sector-specifc uncertainty to other sectors is non-constant, i.e., time varying, and so is the importance of these uncertainties. Naturally, policymakers would need to review the state of the economy in terms of the dominance of a particular uncertainty before designing policies that target a specific sector. In sum however, with the financial sector uncertainty driving macroeconomic and real estate uncertainties, does indeed warrant the strive towards better macroprudential policies. In other words, regulatory frameworks should be developed towards placing more emphasis on mitigating systemic risks in the financial system. In this regard, the macroprudential instruments, namely capital-based instruments (countercyclical capital buffers, sectoral capital requirements and dynamic provisions); asset-side instruments (loan-to-value (LTV) and debt-to-income (DTI) ratio limits); and liquidity-based instruments (countercyclical liquidity requirements) should be monitored continuously (as financial uncertainty evolves over time) while active with regard to their calibration and appropriateness, and be subjected to an (ex-post) analysis of their costs and benefits if and when deactivated (see Tillmann (2015) for detailed discussion in this regard).

As part of future research, it would be interesting to extend our analysis to other countries which have sectors-based uncertainty indices available (see for example, Redl (2017) who develops real and financial sectors-based measures of uncertainty.). This will provide us with the understanding of whether our results are unique to the US or does actually carry over to other countries as well.

[7] Based on the suggestion of an anonymous referee, we also conducted the analysis based on a quantiles-based VAR (QVAR). As can be observed from Table A.3 in the Appendix of the paper, our overall results of the FU being stronger in terms of spillover relative to MU and REU still continues to hold.

Appendix

Table A.1
Unit-Root and stationarity tests.

	REU(1)	REU(3)	REU(12)	FU(1)	FU(3)	FU(12)	MU(1)	MU(3)	MU(12)	RU(1)	RU(3)	RU(12)
Levels												
ADF	– 5.551 ***	– 4.773 ***	– 2.217	– 4.197***	– 4.087***	– 3.754***	– 3.951***	– 4.175***	– 4.024 ***	– 5.019 ***	– 4.689 ***	– 4.155 ***
ERS	– 5.322 ***	– 4.522 ***	– 1.460	– 2.545**	– 2.477**	– 2.298**	– 3.954***	– 4.177***	– 3.994***	– 3.121***	– 2.953***	– 3.155***
PP	– 3.662***	– 2.740*	– 0.638	– 2.958*	– 2.763*	– 2.248	– 2.270	– 2.010	– 1.616	– 3.592***	– 2.931**	– 2.216
ZA	– 7.749***	– 6.973***	– 5.429**	– 5.013*	– 4.897*	– 4.526	– 4.923*	– 5.191**	– 5.245**	– 6.892***	– 6.788***	– 6.485***
NP	– 5.551***	– 4.773***	– 2.217**	– 4.197***	– 4.087***	– 3.754***	– 3.951***	– 4.175***	– 4.024***	– 5.019***	– 4.689***	– 4.155***
KPSS	1.798***	1.594***	1.080***	0.523***	0.519***	0.516***	1.145***	1.119***	0.980***	2.090***	2.050***	1.799***
Returns												
ADF	– 12.579 ***	– 11.823 ***	– 9.070 ***	– 11.430 ***	– 11.102 ***	– 10.044 ***	– 11.509 ***	– 10.190 ***	– 8.657 ***	– 14.064 ***	– 12.509 ***	– 10.970***
ERS	– 12.575***	– 11.748***	– 9.040***	– 7.616***	– 7.300***	– 6.300***	– 9.931***	– 9.717***	– 8.656***	– 7.046***	– 6.976***	– 7.464***
PP	– 13.084***	– 11.369***	– 8.700***	– 12.773***	– 12.309***	– 10.973***	– 11.545***	– 9.602***	– 7.892***	– 14.574***	– 12.220***	– 10.153***
ZA	– 12.760***	– 12.019***	– 9.416***	– 11.737***	– 11.412***	– 10.355***	– 12.017***	– 10.795***	– 9.280***	– 14.474***	– 13.024***	– 11.586***
NP	– 12.874***	– 10.987***	– 8.358***	– 12.696***	– 12.230***	– 10.906***	– 11.283***	– 9.171***	– 7.391***	– 14.473***	– 11.967***	– 9.716***
KPSS	0.016	0.025	0.058	0.045	0.048	0.062	0.049	0.063	0.093	0.016	0.024	0.044

Notes: ***,**,* denote significance level at 1%, 5% and 10%; ADF: Dickey and Fuller (1979, 1981); ERS: Elliott et al. (1996); PP: Phillips and Perron (1988); ZA: Zivot and Andrews (2002); NP: Ng and Perron (2001) and KPSS: Kwiatkowski et al. (1992).

Table A.2
Averaged dynamic connectedness measures using RU instead of MU.

	REU(1)[3]{12}	FU(1)[3]{12}	RU(1)[3]{12}	FROM others
REU(1)[3]{12}	78.37 [68.80] {60.51}	7.00 [11.43] {18.56}	14.63 [19.77] {20.93}	21.63 [31.20] {39.49}
FU(1)[3]{12}	1.58 [4.38] {11.82}	94.49 [90.55] {83.19}	3.94 [5.07] {4.99}	5.51 [9.45] {16.81}
RU(1)[3]{12}	13.91 [20.03] {25.56}	5.77 [8.49] {12.32}	80.32 [71.48] {62.12}	19.68 [28.53] {37.88}
TO Others	15.48 [24.42] {37.38}	12.77 [19.93] {30.87}	18.57 [24.84] {25.92}	46.82 [69.18] {94.18}
NET	−6.15 [−6.79] {−2.10}	7.25 [10.48] {14.06}	−1.11 [−3.69] {−11.95}	TCI
NPDC	0 [1] {1}	2 [2] {2}	1 [0] {0}	15.61 [23.06] {31.39}

Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 12-step-ahead forecast.

Table A.3
Averaged Dynamic Connectedness Using QVAR .

	REU(1)[3]{12}	FU(1)[3]{12}	MU(1)[3]{12}	FROM others
REU(1)[3]{12}	72.09 [60.49] {60.44}	12.78 [20.99] {22.50}	15.13 [18.52] {17.06}	27.91 [39.51] {39.56}
FU(1)[3]{12}	1.31 [3.44] {9.09}	96.62 [93.45] {88.29}	2.06 [3.11] {2.62}	3.38 [6.55] {11.71}
MU(1)[3]{12}	11.88 [15.93] {23.42}	5.77 [8.20] {8.64}	82.35 [75.88] {67.94}	17.65 [24.12] {32.06}
TO Others	13.19 [19.36] {32.51}	18.55 [29.19] {31.15}	17.20 [21.63] {19.68}	48.94 [70.18] {83.33}
NET	−14.71 [−20.15] {−7.06}	15.17 [22.64] {19.43}	−0.45 [−2.49] {−12.38}	TCI
NPDC	0 [0] {0}	2 [2] {2}	1 [1] {1}	16.31 [23.39] {27.78}

Notes: Results are based on a QVAR (White et al., 2015) with lag length of order 1 (BIC) and a 12-step-ahead forecast.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.strueco.2019.09.009.

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