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Dynamic connectedness of uncertainty across developed economies: A time-varying approach

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ABSTRACT

Economic uncertainty has attracted a significant part of the modern research in economics, proving to be a significant factor for every economy. In this study, we focus on the transmission channel of uncertainty between developed economies, examining potential spillover effects between the U.S., the E.U., the U.K, Japan and Canada. Within a time-varying framework our empirical results indicate of a significant spillover of uncertainty from the E.U. to the U.S.

1. Introduction

In wake of the "Great Recession", a large international literature has emerged that has analyzed the (negative) impact of uncertainty on macroeconomic variables and financial markets (see Chuliá et al. (2017) and Gupta et al. (forthcoming b) for detailed literature reviews). In parallel, numerous studies have also analyzed the spillover of uncertainty across economies (see, for example, Colombo (2013), Ajmi et al. (2014), Klößner and Sekkel (2014), Yin and Han (2014), Gupta et al. (2015, forthcoming a), Biljanovska et al. (2017) and Caggiano et al. (2017)). This is important, since if foreign country uncertainties do affect domestic uncertainty, the former is going to have an indirect effect on domestic uncertainty, and prolong its expected direct effects (due to a globalized world) on the domestic economy.

Against this backdrop, we revisit the issue of uncertainty spillovers associated with the U.S., the U.K., Canada, Japan and the E.U., and add to the literature along the following dimensions: (a) Unlike the rolling-window estimation of the popular Diebold and Yilmaz (2012) model to capture spillovers over time, we use a full-fledged time-varying parameter vector autoregressive (TVP-VAR) version as suggested by Antonakakis and Gabauer (2017). This improves the methodology of Diebold and Yilmaz (2012) substantially, because there is no need to arbitrarily set the rolling window-size and there is no loss of observations;[1] (b) Unlike the above-mentioned studies that utilize low-frequency monthly data to analyze uncertainty spillovers, we rely on daily data on uncertainty. Given that uncertainty is considered to be a leading indicator of the macroeconomy (Balcilar et al., 2016), it makes more sense to analyze movements of uncertainty at a higher data frequency, so that the policy makers in the domestic economy know how to react to movements in the foreign uncertainties which are likely to affect the low frequency macroeconomic variables in the future; and, (c) Finally, given that economic decisions and economic variables (macroeconomic and financial) are likely to react differently to short-, medium-, and long-run movements of uncertainties (Barrero et al., 2017), using wavelet theory, we decompose the uncertainty data into its various frequencies, and then in turn, repeat the spillover analysis for each frequency component across the countries considered. In sum, to the best of

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[1] In the Appendix, we report the results from the constant parameter VAR model estimated with a rolling window of 250 observations. The empirical findings are similar to those of the TVP-VAR model, but we do lose a year or so of information in the process.

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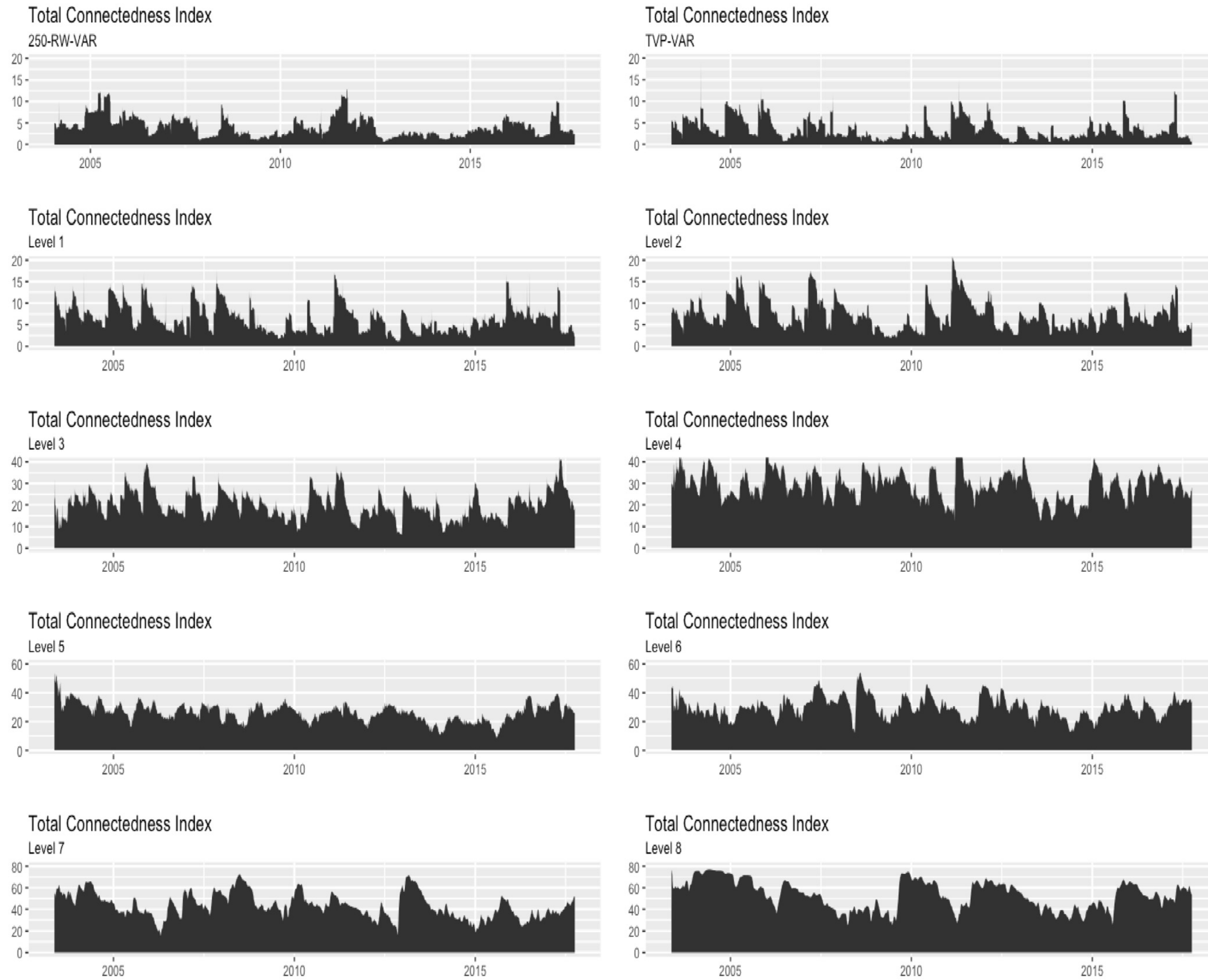

Fig. 1. Total connectedness index of the TVP-VAR model.

our knowledge, this is the first attempt to analyze spillovers of uncertainties within developed economies across both time and frequency dimensions.

The results of our empirical analysis reveal a significant uncertainty transmission from the E.U. to the U.S. Moreover, we detect a change in the spillover effects with the horizon they are associated with, given that in measurements of uncertainty changes in longer horizons tend to be attributed to external drivers of uncertainty.

The remainder of this study is organized as follows. Section 2 describes the empirical methodology employed. The empirical results of our analysis are presented in Section 3. Finally, Section 4 summarizes and concludes this study.

2. Dynamic connectedness based on a TVP-VAR model

To explore the transmission mechanism in a time-varying fashion, we are using the methodology outlined in Antonakakis and Gabauer (2017). According to the Bayesian Information Criterion (BIC) we are employing a stationary TVP-VAR(1) with time-varying volatility

$$Yt = \beta_t Y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \upsilon_t \qquad \upsilon_t \sim N(0, R_t) \tag{2}$$

$$Y_t = A_t \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

where $\boldsymbol{Y}_t$, $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\nu}_t$ are $N \times 1$ vectors and A_t, S_t, β_t and Rt are $N \times N$ matrices. Eq. (3) is the Wold representation of the system. The time-varying coefficients of the vector moving average (VMA) is the fundamental of the connectedness index introduced by Diebold and Yilmaz (2012) using the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD) developed by Koop et al. (1996) and Pesaran and Shin (1998). Our focus is on the h-step error variance in forecasting variable *i* that is due to shocks on variable *j*. Mathematically, it can be written as follows,

$$\tilde{\varphi}^{g}_{ij,t}(h) = \frac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}}{\sum_{i=1}^{N} \sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}} \tag{4}$$

with $\tilde{\varphi}^{g}_{ij,t}(h)$ denotes the *h-step* ahead GFEVD, $\Psi^{g}_{ij,t}(h) = S^{-\frac{1}{2}}_{ij,t} A_{h,t} \Sigma_t \varepsilon_{ij,t}$, Σ_t the covariance matrix for the error $\varepsilon_{ij,t}$ and $\sum_{j=1}^{N} \tilde{\varphi}^{g}_{ij,t}(h) = 1$, $\sum_{i,j=1}^{N} \tilde{\varphi}^{N}_{ij,t}(h) = N$. Based on the GFEVD, we construct the total connectedness index (TCI) representing the interconnectedness of the network, formulated by

$$C^{g}_{t}(h) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\varphi}^{g}_{ij,t}(h)}{\sum_{j=1}^{N} \tilde{\varphi}^{g}_{ij,t}(h)} \times 100. \tag{5}$$