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Global financial interconnectedness: A non-linear assessment of the uncertainty channel

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Abstract

The role of uncertainty in the global economy is now widely recognized by policy-makers but its specific effects on the international financial system are less understood. In this paper we assess the impact of uncertainty fluctuations on the interconnectedness within the international system of equity prices. In this respect, we extend the measure of connectedness put forward by Diebold and Yilmaz (2009) by allowing for non-linear effects through the estimation of a non-linear Threshold VAR model whose regimes depend on the level on uncertainty. Results show that high uncertainty tends to generate more connectedness among equity indexes of a set of advanced and emerging countries. From an economic policy point of view, this result suggests that in the presence of high uncertainty, an adverse financial shock in a specific country is likely to propagate more widely and more strongly to the whole financial system. This result advocates for a close real-time monitoring of uncertainty measures.
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1 Introduction

The diffusion of a financial crisis is one of the greatest fears among international financial authorities. The last Global Financial Crisis has made clear that looking at financial institutions in isolation gives an incomplete and misleading assessment of the impact of shocks to the financial system. Indeed, even a country with strong macroeconomic fundamentals can be hit by a negative financial shock stemming from other countries and thus experience severe financial turmoil. In this respect, the recent economic literature has investigated financial contagion in the form of networks by looking either at contractual agreements between banks or equity stock market comovements (see Eun and Shim, 1989, Braverman and Minca 2014, Acemoglu et al. 2015, and Brunetti et al. 2015 among others).[1] In this literature, financial networks are mainly established between banks or mutual funds and are often considered as self-organized without accounting for the influence of external forces. Another strand of the literature, without using any explicit network structure, tries to analyze the channels through which financial disruption is likely to spread across the world. For example, Glick and Rose (1999) and Weber and van Rijckenghem (2001) highlight the role played by usual channels, such as the trade channel and financial flows. Some studies have also stressed that uncertainty is also likely to constitute a channel for markets' connectedness (see Kaminsky and Reinhart 2000, Rigobon and Wei 2003, Kannan and Köhler-Geib 2009). Especially, they show that financial contagion is quicker and stronger when it has not been anticipated by financial markets. In the same vein, Kodres and Pritsker (2002) theoretically demonstrate that investors reallocate their portfolio positions when facing large uncertainties around their macroeconomic expectations. A widely accepted theoretical definition of uncertainty is given by Knight (1921), who distinguishes between risk, described as a situation in which the probability distribution over a set of events is known, and uncertainty, a situation in which people are unable to forecast the likelihood of events happening (see also Bloom 2014, for a review on this topic).

However, as uncertainty is not directly observable, the concepts of risks and uncertainty are not easy to disentangle in practice. In this respect, various empirical measures have been proposed in the recent literature, ranging from financial uncertainty, measured by market volatility, through macroeconomic uncertainty, as proposed for example by Jurado et al. (2015) and Scotti

[1] See section 2 for a review of literature.

(2016), to economic policy uncertainty, as defined by Baker et al. (2016).[2] In the empirical part of this paper, we will use various measures of uncertainty to check the robustness of our results.

Our paper aims at bridging the gap between the literature on uncertainty and the one on connectedness. On the one hand, we evaluate connectedness among international financial markets using a network approach. On the other hand, we investigate uncertainty as a potential channel shaping interconnections between markets. Unlike the traditional network literature, this paper is more macro-oriented since we look at contagion between countries (i.e. equity indexes) rather than between specific classes of assets. This framework seems to be more suitable when looking at global systemic risks and the effects of exogenous macroeconomic shocks on the pattern of connections. Regarding exogenous factors our assumption goes to the role that incomplete information about future outcomes (i.e. forecasting errors) plays on financial actors. The aim of this paper is threefold: (i) investigate empirically interconnectedness between international financial markets, (ii) evaluate financial network stability over time through a non-linear model and (iii) test for financial system resilience to uncertainty shocks.

Our empirical framework relies on the network approach developed by Diebold and Yilmaz (2014) to measure financial asset connectedness, based on the variance decomposition of the h-step-ahead forecasts from a VAR model. This approach enables to calculate the degree of connectedness within a system of individuals by computing a network index ranging between 0 and 100. As a side result, this approach leads to a classification of individuals between net givers, i.e., individuals who generate financial spillovers, and net receivers, i.e., individuals who receive financial spillovers. As an innovation, we propose a non-linear version of this approach by implementing a Threshold-VAR (TVAR) model that enables a different set of parameters to be considered depending on the values of an observed transition variable. We further assume that uncertainty is the transition variable that governs parameter switches within the VAR model. This hypothesis is formally tested by using Log-Likelihood ratio tests and is widely accepted. To the best of our knowledge, this non-linear extension of the Diebold-Yilmaz approach to cross-border interconnectedness analysis is novel in the literature. We apply this approach to a set of monthly stock markets indices for 13 major countries (the U.S., the

[2] Other approaches, such as that developed by Carriero et al. (2016), simultaneously estimate uncertainty measures and their impact on the economy by accounting for both financial and macroeconomic uncertainty. We also refer to Ferrara et al. (2017) for a review of various uncertainty measures and how to interpret them.

U.K., 7 European countries and 4 emerging markets) over the last 20 years. We first measure connectedness by estimating linear coefficients in a VAR model as a benchmark. Then, we test for non-linearity and present evidence of a threshold effect in uncertainty by using alternative measures of uncertainty (financial, macroeconomic, economic policy). Finally, the network index of Diebold-Yilmaz (2014) is computed for each of the two regimes, providing us with an indication of the geographical origin and destination of the financial contagion and how it varies with respect to the high- and low-uncertainty regimes.

Some salient facts emerge from our empirical results. First, the standard linear Diebold-Yilmaz analysis reveals that there is a fairly strong connectedness within global equity markets. This high degree of connectedness is driven by financial spillovers among advanced economies, the U.S. being the main driver, while emerging countries appear much less financially interconnected. In addition, although China is often considered as a regional leader, our results do not support the view that it is a global driver of financial interconnectedness, at least over the considered period of time. Then, by allowing for non-linearity, we get that the degree of connectedness within the global financial system is stronger when uncertainty is high, and conversely. This finding is supported regardless of the proxy for uncertainty used, in line with our intuition. Second, within the linear system of 13 countries, we identify the U.S. and the UK as net givers to the system; China and Germany are rather neutral, while all other countries are net receivers. Additional results show that when Economic Policy Uncertainty (EPU) in Europe is in its high regime, Germany shifts from a position of net giver to net receiver, pointing out its nodal role in Europe.

Evidence of stronger connectedness within the global financial system during high uncertainty episodes can be useful in many ways for policy-makers. First, it may be useful for financial regulators to better evaluate the potentially contagious (and thus systemic) features of a particular crisis by integrating a real-time monitoring of uncertainty measures. Second, those results represent a strong call for financial regulators and authorities to implement adequate policies to limit uncertainty. For example, financial regulations intended to guarantee the stability of the banking system reduce uncertainty and hence are likely to limit the transmission of a crisis. Reducing uncertainty can also be achieved by maintaining predetermined or pre-announced policy measures (for example forward-guidance or credible multi-years consolidation plans), rather than applying discretionary policies. Third, we can infer from our results that a persistently high level of economic policy uncertainty is likely to constitute a favorable environment for a financial shock to spread more widely, especially when the country has been characterized as a net giver to the global financial system (i.e.: the U.S. or the UK).

The paper proceeds as follows. The second section reviews some papers on network interconnectedness literature, with particular emphasis of the role of uncertainty on network stability. Our empirical strategy relying on the extension of the approach put forward by Diebold and Yilmaz (2009, 2014) is presented in section 3. Data and uncertainty measures are presented in section 4, whereas section 5 reports the empirical results. Section 6 presents some robustness checks and additional results. In particular we perform sensitivity analyses to model specification and time horizon, then achieve a geographical analysis using the novel database of Scotti (2016) and investigate the specific consequences of the Brexit-related uncertainty. We draw some conclusions and tentative policy recommendations in section 7.

2 Network interconnectedness and uncertainty

2.1 Literature review on network interconnectedness

Since the seminal paper of Allen and Gale (2000), network structures have become a suitable framework to evaluate contagion in interconnected financial systems. In the network literature, financial interconnectedness is usually defined as a broad set of relationships among financial markets participants.[3] The nature of the relationships can widely vary from direct contractual agreements such as those stemming from interbank lending and borrowing (i.e. physical trading networks) to economic connections through common assets holding[4] inferred from market price data (i.e. correlation networks of stock prices). From a technical point of view, the former approach is usually based on balance sheets of banks or mutual funds while the latter is inferred from equity stock returns (see Kara et al. 2015). From an economic point of view, it is now generally accepted in the literature that correlation networks are the main source of systemic risk among financial institutions since interconnectedness is driven by common factors (see Eun and Shim, 1989, Elsinger et al. 2006, Braverman and Minca 2014, and Brunetti et al. 2015

[3]While a number of research papers usually looked at bank interconnectedness, participants can be of different natures such as institutions, countries, firms, etc.

[4]This form of contagion occurs via transmission of shocks such as a sudden drop in the flow of revenues to one bank which affects other institutions connected to it through financial linkages (see Cabrales et al. 2015 for a discussion).

among others). [5] Focusing on equity market returns, our paper is related to the correlation network literature on which contagion mechanism between participants may work as follows. Consider two institutions A and B that each holds the same asset in their portfolios. Suppose now that an exogenous shock (whatever its origin[6]) forces institution A to liquidate the asset, the price of the asset will decline and modify the value of the portfolio of the other institution B generating networks between institutions. Of course, the origin of the exogenous shock may be common to all participants and sufficiently larger to affect all institutions simultaneously forcing A and B to liquidate the asset and rebalancing their portfolios. Our focus on market returns rather than accounting framework is further motivated by the desire to incorporate the most current market information to investigate financial interconnectedness (see Billio et al. 2012 for that point).

In this burgeoning literature on correlation network, most papers are focused on microeconomic interconnectedness financial systems such as those occurring between firms in a specific country. Braverman and Minca (2014) for instance investigate how inter-relations between U.S. equity mutual fund are generated by common asset holdings and liquidity shocks. They further develop a vulnerability index that equals to the sum of funds' exposures through common asset holdings to other funds. They find that the index is useful in predicting returns in periods of mass liquidations. In the same vein, Cont and Wagalath (2013) develop a simple tractable model to investigate the impact of "fire sales" on variance and correlation of mutual fund assets. [7] By decomposing realized covariance into a fundamental and a liquidity-dependent component, they show that excess covariance leads to endogenous risk for large portfolios during financial and economic turmoil limiting the benefits of diversification when needed. In the spirit of Allen and Gale (2000) on the benefit of interconnectedness on financial stability [8], Cabrales et al. (2014) investigate the trade-off between higher risk-sharing and greater exposure to contagion when the connectivity increases. The idea of the paper is to study how the capacity of the system to absorb shocks depends on the pattern of interconnections among firms. They

[5] Brunetti et al. (2015) investigate both physical and correlation networks between European interbank markets and shows that during the recent crisis period, physical network connectedness dropped significantly while correlation networks increased.

[6] By definition, the shock should be sufficiently larger to force the institution to liquidate the asset and generate contagion (see McTier et al. 2013, Puliga et al. 2014).

[7] Fire sales denote the liquidation of large position by market participants.

[8] Allen and Gale (2000) show that more complete networks are less susceptible to contagion since they provide better risk diversification than incomplete networks.

show that contagion among firms, as a pathologic disease, originates from an exchange of asset among them (i.e. portfolio reallocation). Overall the literature claims that, by holding similar portfolios, institutions are necessarily dependent and exposed to the same exogenous financial and economic shocks.[9] The origin of the exogenous shock at a microeconomic level may be of several forms such as leverage targeting (see Adrian and Shin 2010), bank run (Gorton and Metrick 2012), investor flows (Coval and Stafford 2007) etc. Unlike previous papers that focus on banks, firms or insurances, we take a more global perspective by assuming that correlation networks between risky assets corresponds to an individual country's entire asset market (i.e. equity index). In this framework, the contagion mechanism from one equity market to others reflects contagion between countries. Network interconnectedness here indicates global financial connection between countries whatever the composition of the considered equity indices. Our assumption is that this framework is more suitable to evaluate macroeconomic systemic risk rather than interconnectedness at microeconomic level especially in case of macroeconomic exogenous shocks.

2.2 Uncertainty shocks and network stability

While previous research assumes static network overtime, it turns out that the topology of financial markets interconnections may evolve dynamically. It means that interconnections among assets at a given date are not necessarily the same at another one. Against this background, Billio et al. (2016) have recently proposed a statistical approach based on Granger causality and MS-GARCH to deal with such dynamic networks. Treating network as information diffusion, they show that some structures inherent to the system, such as the number of connections among stock exchanges and their associated strengths, are regime-dependent. The dynamic of financial markets networks is however assumed to be endogenous in the sense that instability of the system emerges without any external shocks. This assumption leaves aside the question of the diffusion of exogenous shocks on the network stability, while external forces may shape the resilience of the network structure.

As regards exogenous factors, evidence recently blossomed as regards the role of uncer-

[9]Another branch of the literature on financial networks looks at contractual agreement among firms (see Gai et al. 2011, Acemoglu et al. 2015, among others). Some others consider both correlation and physical networks (see Brunetti et al. 2015).

tainty about the future state of the economy as a driver of macroeconomic and financial fluctuations. At a macroeconomic level, the effect of uncertainty has been widely documented in the economics literature, especially with respect to the mechanism whereby it affects growth and investment, which has been extensively discussed both theoretically and empirically (see Bloom 2014, and Ferrara et al. 2017, for a review). Overall, studies generally agree that high uncertainty gives firms an incentive to delay investment and hiring under the irreversibility condition or fixed costs through an *option value to wait* (see Bernanke 1983, Bloom et al. 2007, and Bloom 2009, 2014).

In the financial markets' literature, while theoretical studies have highlighted that uncertainty constitutes a propagation channel for financial connections (see Kodres and Pritsker 2002, Kaminsky et al. 2003, Rigobon and Wei 2003, and Mondria and Quintana-Domeque 2012, inter alii) little empirical evidence exists.[10] It is supposed that uncertainty influences investors' behaviors leading them to re-allocate their portfolio positions, amplifying thus financial markets contagion (see Kodres and Pritsker 2002, and Connolly et al. 2005). Uncertainty not only changes economic agents behaviors, but it is also a huge shock to the system on itself since it is often counter-cyclical. Yet, as stressed by Allen and Gale (2000), it turns out that highly interconnected networks are more resilient to small exogenous shocks but not to large ones. This means that a large shock is likely to shift a well interconnected system to another equilibrium. In this paper, we empirically investigate the role that uncertainty can have on network stability. Specifically, we assess to what extent the level of uncertainty is likely to shape the connectedness of international financial markets.

3 Econometric framework: Extension of the Diebold-Yilmaz network index

In this paper, we rely on econometric time series modelling to assess financial network connectedness. [11] In the literature, two recent econometric approaches have been put forward to

[10]Two notable exceptions can be nevertheless found. Connolly et al. (2005), who examine whether time variation in the comovements of daily stock and Treasury bond returns can be linked to stock market uncertainty, as well as Alfaro, Bloom and Lin (2016). Hasse (2016) further shows using stability tests that uncertainty, complexity and networks structure are cobreaking, supporting hence the idea of strong relationship between them.

[11]See Adamic et al. (2010) and Bech and Atalay (2011) for a review of econometric measures and financial applications.

estimate network connectedness. First, Billio et al. (2012) propose a two-step procedure which consists in quantifying the degree of connectedness between financial assets through principal components analysis and then investigate the directionality within the system by Granger causality tests. Second, Diebold and Yilmaz (2014) develop a network approach based on variance decomposition of vector auto-regressive (VAR) model. While both measures are in some sense quite close, for several reasons variance decomposition is more appealing in our context than using pairwise Granger causality. Indeed unlike VAR setting, Granger causal approach is directional but exclusively pairwise and unweighted, tests zero versus non-zero coefficients with somewhat arbitrary significance levels and does not track the magnitude of non-zero coefficients.[12] On the other hand, it is well known that variance decomposition and impulse response analysis may suffer from identifying assumptions inherent to VAR setting. However, this restriction can be partially mitigated by careful robustness checks as we do in the empirical part of the paper.

3.1 Assessing connectedness using the Diebold-Yilmaz approach

Our approach is based on the Diebold and Yilmaz (2014)'s definition of interconnectedness as the share of forecast error variation in one market due to shocks arising elsewhere. In order to provide an analysis of interconnectedness in a multivariate setting across N various countries over time, where N is large enough to adequately represent a large proportion of the world, let's start with the following covariance-stationary VAR representation of dimension p:

$$x_t = B(L)x_{t-1} + \xi_t, \tag{1}$$

where x_t is a N-vector of equity market returns, $B(L)$ is a lag-polynomial of matrices and $\xi_t \sim N(0, \Sigma_\xi)$ is a vector of independently and identically distributed disturbances. Assuming weak stationarity, x_t follows the infinite-order moving-average representation:

$$x_t = \sum_{l=0}^{\infty} A_l \xi_{t-l}, \tag{2}$$

where $A(L) = (I - B(L))^{-1}$, and $A_l = 0$ for $l \leq 0$.

After obtaining the moving-average representation, Diebold and Yilmaz (2014) rely on variance decompositions to compute financial interconnectedness. Variance decompositions

[12] See Diebold and Yilmaz (2014) for a discussion on those points.

allow an assessment of the fraction of the H-step-ahead forecast error variance in forecasting one variable with respect to shocks from other variables in the system. However, this approach calls for the identification of structural shocks by imposing a sufficient number of identification restrictions to cope with contemporaneous correlated VAR innovations. Cholesky factorization is often used to achieve this goal but requires some limitations that depend on the VAR-ordering specification. The generalized forecast error variance decomposition is also used as an alternative invariant counterpart when there is a lack of credible identification restrictions (see Koop et al. 1996 and Pesaran and Shin 1998). The main difference between the two approaches is that while in the former shocks are uncorrelated and carry an economic meaning, in the latter they may be correlated and the interpretation is somewhat ambiguous, as share sums are not necessarily unity. As in Diebold and Yilmaz (2009), our preference goes to the Cholesky decomposition.[13]

In this respect, let's rewrite equation (2) as follows:

$$x_t = \sum_{l=0}^{\infty} \Theta_l \omega_{t-l}, \tag{3}$$

where $\omega_t = P^{-1}\xi_t$ is the orthogonalized error for which P^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ξ_t. $E(\omega_t \omega_t') = I$, meaning that shocks of ω_t are uncorrelated.

Following Diebold and Yilmaz (2014), for any variable x_t^j in the system, its contribution to variable x_t^i's H-step-ahead forecast error variance is given by:

$$\varphi_{ij}(H) = \sum_{h=0}^{H-1} \left(e_i' \Theta_h e_j\right)^2, \tag{4}$$

where e_j is the selection vector with the j-th element being unity and zeros elsewhere, and Θ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the orthogonalized model. Hence, $\varphi_{ij}(H)$ can be interpreted as a measure of pairwise directional connectedness from j to i at a given forecast horizon H. In the results, we express those figures in percentage terms, such that for any country i, $\sum_{j=1}^{N} \varphi_{ij}(H) = 100$.

To facilitate the analysis from the $N \times N$ tables of pairwise connections, we also examine two measures to assess (i) the contribution that a country i receives from the rest of the world

[13] See Section 6.1.2 for a discussion and robustness checks.

(RoW)[14], denoted $C_{i\leftarrow RoW}(H)$, and (ii) the contribution of a country j to the rest of the world, termed $C_{j\rightarrow RoW}(H)$. Those measures are defined such that, for all countries i, j,

$$C_{i\leftarrow RoW}(H) = \sum_{j=1, j\neq i}^{N} \varphi_{ij}(H) \tag{5}$$

and

$$C_{j\rightarrow RoW}(H) = \sum_{i=1, i\neq j}^{N} \varphi_{ij}(H). \tag{6}$$

Obviously we have that for any country i, $C_{i\leftarrow RoW}(H) = 100 - \varphi_{ii}(H)$.

A useful measure, often used in this type of analysis, is the *net contribution* of a country i to the system, obtained by analyzing how much this country contributes to the system minus how much it receives from the system. For any country i, this measure is intuitively given by

$$C_i(H) = C_{i\rightarrow RoW}(H) - C_{i\leftarrow RoW}(H) \tag{7}$$

Based on this measure, we can classify countries between net givers, i.e., countries that contribute more to the system than they receive, for which $C_i(H) > 0$, and net receivers, i.e., countries that receive more from the system than they contribute, for which $C_i(H) < 0$. Overall, it is easy to see that $\sum_{i=1}^{N} C_i(H) = 0$.

Finally, a measure $C(H)$ of the system-wide connectedness can be obtained to assess the degree of connectedness of the whole system. This measure will be useful to compare systems depending on the level of uncertainty. It is obtained by either averaging all the contributions that countries receive from the rest of the world or by averaging all the contributions countries give to the rest of the world:

$$C(H) = \frac{1}{N}\sum_{i=1}^{N} C_{i\leftarrow RoW}(H) = \frac{1}{N}\sum_{j=1}^{N} C_{j\rightarrow RoW}(H) \tag{8}$$

3.2 Non-linear extension of the Diebold-Yilmaz approach

The idea of this paper is that uncertainty might be a potential driver of the dynamics within equity markets' networks. Allowing for shifts in interconnectedness with respect to uncertainty, we propose to extend to a nonlinear framework the standard approach of Diebold and Yilmaz

[14] Assuming that the world is proxied by all the countries within the system.

(2014). Starting from the standard linear setting, we assume that uncertainty may be a nonlinear propagator of shocks across equity markets that affects the pattern of connectedness between price returns. We thus assume that the parameters of the VAR model given in equation (1) can switch over time from one regime to the other, depending on a threshold controlled by a specific transition variable. In this respect, we replace equation (1) with the following Threshold VAR (TVAR) model (9) whose parameters switch from a low-uncertainty regime to a high-uncertainty regime:

$$x_t = B_1\left(L\right) x_{t-1} + B_2\left(L\right) x_{t-1} I_t\left(u_{t-d} \geq \mu\right) + \xi_t, \tag{9}$$

where x_t is a vector of endogenous variables containing the stock price indexes of N countries. The lag polynomial matrices $B_1\left(L\right)$ and $B_2\left(L\right)$ reflect structural relationships within each of the two states and ξ_t denotes the vector of orthogonalized error terms. u_{t-d} is the d-lagged threshold variable, which serves as a measure of uncertainty in our setting. We consider the lagged transition variable to avoid potential endogeneity issues that would bias our estimation.[15] $I_t\left(u_{t-d} \geq \mu\right)$ is an indicator function that equals 1 when $u_{t-d} \geq \mu$ and 0 otherwise, where μ denotes the threshold uncertainty critical value that has to be endogenously estimated. In other words, two states are identified: the low-uncertainty state corresponding to a weak degree of uncertainty ($I_t(.) = 0$) and the high-uncertainty state related to a high degree of uncertainty ($I_t(.) = 1$). The coefficients of the TVAR model are allowed to change across states depending on the level of uncertainty. Note that in our framework we only allow for two regimes of uncertainty, but in theory this framework can be easily extended to three or more regimes. The only empirical issue is that each regime has to be frequently visited; otherwise, a given regime cannot have sufficient observations to correctly estimate the number of parameters in the TVAR model.

Once tests for the regime have been conducted and the coefficients and covariance matrix have been saved from the estimation step, the forecast error variance decomposition can be carried out, conditionally to each regime of uncertainty. That is, for any horizon H, in the regime 1 of low uncertainty $\varphi_{ij}^1(H)$ can be computed based on equation (4) and similarly, in the regime 2 of high uncertainty $\varphi_{ij}^2(H)$ can be computed based on the same equation.

[15] In so doing, we also assume that uncertainty is exogenous with respect to financial markets interconnectedness (see Ludvigson et al., 2015, or Caldara et al., 2016, for further details on the endogenous or exogenous nature of uncertainty).

Relying on those latter measures, the contributions received by a country i from the RoW, conditionally on regimes of low and high uncertainty, that is $C^1_{i \leftarrow RoW}(H)$ and $C^2_{i \leftarrow RoW}(H)$ can be easily computed from equation (5). Symmetrically, the contributions given by a country j to the RoW, conditionally on regimes of low and high uncertainty, that is $C^1_{j \rightarrow RoW}(H)$ and $C^2_{j \rightarrow RoW}(H)$ can be computed from equation (6). Last, the global connectedness measures in each regime, namely $C^1(H)$ and $C^2(H)$, derive from equation (8).

4 Data

In this section, we describe the database that we use in the empirical part of the paper. To have an overview of financial interconnectedness across international financial markets, we consider a dataset of 13 equity indices classified into two categories: (i) advanced countries (the U.S., the U.K., Germany, France, Italy, the Netherlands, Spain, Portugal, and Greece) and (ii) emerging countries (China, Brazil, Russia and India). All series are sampled at a monthly frequency starting in January 1998 and ending in December 2015, thereby covering several periods of economic and financial turmoil with common or idiosyncratic consequences, such as the Argentine economic crisis (1999-02), the dot-com bubble (2001), the global financial crisis (2007-08), and the European sovereign debt crisis (2011-13). To achieve stationarity, all the series have been transformed into first-logarithmic differences (i.e., log-returns).[16]

Choosing the adequate measure of uncertainty is a more complex issue since this concept can take several forms. Thus we consider three various measures of uncertainty: (i) a measure of financial uncertainty based on implied volatility, (ii) a measure of macroeconomic uncertainty based on aggregate macroeconomic information, and (iii) a mesure of economic policy uncertainty estimated from news-based metrics. Since each proxy is related to different components of uncertainty, they may have different impacts on international financial networks.

As regards financial uncertainty, we employ the Chicago Board of Option Exchange VXO index of percentage implied volatility based on a hypothetical at-the-money S&P100 option. This proxy, as the VIX index based on the S&P500, is widely used in the literature since it refers to the market's expectation of volatility implicit in the prices of options (see Connolly et al. 2005 and Bloom 2009, among others).

However, as stressed by Jurado et al. (2015), most of the commonly used approaches based

[16]See Table A1 and Figure A1 in online Appendix for further details on the dataset.

on the implied or realized volatility of stock market returns vary over time due to several factors (risk aversion, leverage effect, etc) even if there is no significant change in uncertainty. In other words, Jurado et al. (2015) note that fluctuations that are actually predictable can be erroneously attributed to uncertainty. To overcome this constraint, those latter authors define a measure of macroeconomic uncertainty based on the common variation contained in a large database of macroeconomic and financial monthly indicators, reflecting the state of the U.S. economy, and propose to remove the forecastable component of the considered series before computing the conditional volatility. This measure has the advantage of agreeing with uncertainty-based business cycle theories that assume common variation in uncertainty across a large number of series.[17]

Turning to economic policy, concerns about uncertainty have intensified in the wake of the global financial crisis. For instance, the Federal Open Market Committee (2009) and the IMF (2012, 2013) argue that uncertainty over U.S. monetary policies contributed to a steep economic decline in 2008-09 (see also Stock and Watson 2012). Other studies also show that economic policy uncertainty played a non-negligible role in explaining the slump in investment during the recovery (see, for example, Bussiére et al. 2015). To investigate the role of economic policy uncertainty on financial markets networks, we use the Economic Policy Uncertainty (hereafter, EPU) index developed by Baker et al. (2016) that reflects the frequency of articles in leading U.S. newspapers that contain the following triple: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more policy-relevant terms.[18] Together with the U.S. EPU, we also investigate how both European and Chinese EPUs could contribute to systemic risks.[19]

5 Main results on international financial markets' connectedness

5.1 Connectedness through the standard Diebold-Yilmaz approach

In the first part of our empirical analysis, we use the standard linear approach of Diebold and Yilmaz (2014) for a set of 13 international equity markets, in order to obtain benchmark results on global financial markets' connectedness. Table 1 reports results for international pairwise

[17] The proxy is freely available on Ludvigson's homepage http://www.econ.nyu.edu/user/ludvigsons/

[18] As regards the U.S., the terms used are: "congress", "deficit", "Federal Reserve", "legislation", "regulation", or "White House". See Baker et al. (2016) for further details.

[19] The European EPU reflects economic policy uncertainty in Germany, France, Italy, Spain and the U.K. and is drawn from two newspapers per country (in their native languages). The Chinese EPU is based on the South China Morning Post, Hong Kong's leading English-language newspaper.

directional connectedness $\varphi_{ij}(H)$ between countries for $H = 5$ months and shows some stylized facts.[20] It also tests the significance of each country's contribution using bootstrap confidence bands.[21] First, we get that the degree of system-wide connectedness is relatively high, $C(H)$ being equal to 68.3%. Some blocks of high pairwise directional connectedness $\varphi_{ij}(H)$ appear in the table, especially between the U.S. and European countries (Germany, France and the U.K., at more than 50%). The U.S. case is notable in the sense that the country is extremely closed as it does not receive much from other countries: its contribution to its own variance is $\varphi_{ii}(H) = 75.3\%$. However, the U.S. substantially contribute to the variance of other countries, especially advanced economies. The relationships with the four BRIC countries (Brazil, Russia, India, and China) is much lower, especially with China (only 8.6% of the Chinese variance is explained by the U.S.). This stylized fact is related to the fact that China cannot be considered as an open-market economy over the sample period. The Chinese capital account is indeed very closed, as can be seen in its high contribution to its own variance ($\varphi_{ii}(H) = 70.3\%$). Thus, the role of China in global financial markets networks appears to be very limited. Though it is often considered as a regional leader, our results show that China does not appear as an international leader over the whole period 1998-2015. So, if the Chinese economy is now a driver of the global economy, as often read in the media, then it has been since only very recently.

Within the global financial system, the *net contributions* $C_i(H)$ give a broad view of the role of each country. In this respect, as expected, the U.S. ($C_i(H)$=428) is by far the main driver of global financial markets, as it contributes much more than it receives. To a lesser extent, the U.K. ($C_i(H)$=34) is also a *net contributor* to the system. China ($C_i(H)$=2) appears to be relatively neutral and non-significant; as already mentioned its independence vis-à-vis the global financial system has to be related to its closed financial account. All other countries in the system are *net receivers*. The main receivers appear to be small open economies that are usually identified in the literature as followers either because their markets are not mature enough or because of their relatively small size, such as the Netherlands, Spain, Portugal or Greece.

We now turn to the row and column sums "FROM" and "TO", which denote the share of shocks received from (resp. given to) financial markets in the total variance of the forecast error

[20] The choice of H is discussed in section 6.

[21] We choose to report results for 10,000 bootstrap replications. Our results are however robust to the number of replications.

for each country, respectively. The dispersion of the "FROM" column ranges between 25% for the U.S. and 91% for France (reflecting the substantial openness of France to other countries in the system, mainly the U.S., the U.K. and Germany) and is lower than the dispersion in the "TO" row, which ranges between 16% for Portugal to 453% for the U.S.[22] As an additional result, we divide the countries into two sub-groups: advanced countries and the BRICs. Comparing the results for the sub-groups presented in Tables B1 and B2 in online Appendix, we confirm that total spillovers within emerging equity markets are much lower than within advanced markets (24% against 72%). It further reveals that the *net contributor* position of a given country is relative to the considered system. Indeed, among advanced economies, the hierarchy in the system is similar to the one of the global system, but among the reduced BRIC system, China and Brazil are now *net contributors*.

5.2 Financial markets and uncertainty: Evidence of a non-linear relationship

Our hypothesis, as written in equation (9), is that uncertainty may affect financial networks and that the propagation mechanism is non-linear and characterized by two regimes of high and low uncertainty. To check this hypothesis, we first test for non-linearity in three various groups of countries, namely global, advanced and emerging markets. We will further test for different measures of uncertainty as transition variable to determine whether the source of uncertainty matters (economic policy uncertainty, financial uncertainty and macroeconomic uncertainty). In practice, testing for non-linearity is not straightforward as there is a well-known identification issue under the null hypothesis of no threshold effect. We test for a threshold effect by relying on a non-standard inference procedure over all possible threshold values in a least squares regression framework, using a grid-search procedure over all possible values of the threshold variable.[23] Using Hansen (1996)'s procedure, we generate three Wald-type statistics to test for the null hypothesis of no difference between states.[24] Using the bootstrap procedure of Hansen (1996) to simulate distribution and conduct inference, the estimated threshold values

[22]As noted above, by definition of the column "FROM" is equal to 100% minus the diagonal elements, whereas the row "TO" is not constrained to sum to 100%.

[23]To ensure a sufficient number of data points for the estimation procedure in each regime, the grid is trimmed at 15% as is common in the literature.

[24]The three statistics are (i) the maximum Wald statistic over all possible threshold values (sup-Wald), the average Wald statistic over all possible values (avg-Wald), and a function of the sum of exponential Wald statistics (exp-Wald).

are those that maximize the log-determinant of the variance-covariance matrix of residuals. Table 2 in the main text and Tables C1 and C2 in online Appendix contain threshold test results for global, developed and emerging markets, respectively. Together with linearity tests, we also report proportion and average duration of the high-uncertainty regime. We reject linearity for all models (regardless of the measure of uncertainty and the groups of countries considered), meaning that a non-linear relationship between equity markets and uncertainty is likely to be at play. Comparing first the results for advanced and emerging markets from Tables C1 and C2, we find that the threshold values of the uncertainty proxies are quite different.[25] The frequencies of the high-uncertainty regime (*i.e.*, when the uncertainty measures exceed the corresponding threshold values) are quite different between groups of markets. For instance, we get that periods of high uncertainty are more frequent, for both financial and macroeconomic uncertainty, in advanced markets than in emerging markets (advanced markets are in the high regime 26% and 40% of the time, when considering financial and macroeconomic uncertainty, respectively, against only 20% and 17% for emerging markets). Accounting for economic policy uncertainty, both in Europe and in the U.S., as a threshold leads to more frequent high-uncertainty periods in emerging markets (55% and 45%, respectively) than in advanced ones (24% for both). This result is in line with the literature on the global effects of U.S. economic policy, especially monetary policy, that is likely to affect emerging market asset prices (see for example Eichengreen and Gupta 2014, Aizenman et al. 2015, and Aizenman et al. 2016). Interestingly, we point out here that economic policy in Europe is also likely to affect financial markets in BRIC countries. In terms of average duration[26], periods of macroeconomic uncertainty last longer (approximately 13 months for both groups of countries), underlining the higher persistence of macroeconomic uncertainty by comparison with financial and economic policy uncertainty.

5.3 Financial markets connectedness in low and high regimes of uncertainty

Now that evidence of non-linearity in the relationship between uncertainty and financial markets dynamic has been put forward, we compute the non-linear version of the Diebold-Yilmaz index described in Section 3.2 by estimating the TVAR model and decomposing the forecast error

[25] While we cannot directly compare each threshold value from one group (say, developed markets) since the uncertainty measures are not in standardized units, it is possible to compare the values for different groups.

[26] The average duration of high-uncertainty periods is calculated by dividing the total number of months in the high-uncertainty regime (when the proxy is above the threshold) by the length of the whole sample.

variance in each regime of low and high uncertainty. To save space, we only focus on the results for global equity markets, namely the full set of countries.[27] In Tables 3 to 7, we report the results for the nonlinear Diebold-Yilmaz index in high- and low-uncertainty regimes for international equity markets. We are able to evaluate pairwise and system-wide connections within the global equity market with respect to the level of uncertainty (i.e. in low- and high-uncertainty states).

Our results reveal that accounting for non-linearity when evaluating financial markets networks is of crucial importance since both system-wide and pairwise connectedness differ according to the degree of uncertainty. Indeed, on average over the five uncertainty measures, global connectedness ($C(H)$) increases by 11.3 percentage points (p.p.) when moving from the low- to the high-uncertainty state. There is however some heterogeneity. For example, when U.S. macroeconomic uncertainty is taken as transition variable, global connectedness goes from 69.6% in the low regime to 84% in the high regime (+14.4 p.p.). But this increase is a bit less pronounced when the financial volatility is considered as transition variable (an increase of only 4.3 p.p., from 69.8% to 74.1%). Computing 95% confidence intervals around system-wide connectedness enables to test whether there is a significant increase when shifting uncertainty. Confidence bounds are presented below the degree of global connectedness in tables 3 to 7. From those results, we can conclude that the increase in connectedness is generally statistically significant at usual level, except when financial volatility drives the degree of uncertainty; in that case we cannot reject the null of no increase. At a more granular level, as in the benchmark linear model, the behavior of the U.S. and China vis-a-vis their own variances is quite specific in the sense that they are both very closed markets that do not receive much from other countries. In the low-uncertainty regime, their own variance contributions are of the same order as those in the benchmark model (approximately 75%). However, when moving into high-uncertainty states, both countries become more open. For instance, in periods of high U.S. macroeconomic uncertainty, the U.S. auto-contribution goes down from 74.6% in the low regime of uncertainty to 27.8% in the high regime. This movement is also similar for China (from 72.4% to 28.1%). This reflects the fact that an increase in U.S. macroeconomic uncertainty is a strong mover as it is generally associated to U.S. economic recessions. It seems that in that case, we observe a rebalancing of the financial system away from the U.S. An increase in the Chinese EPU leads

[27]Results for developed and emerging sub-groups go in the same direction, results being available from the authors upon request.

to similar results, acting also as a rebalancing driver within the global equity market.Let us turn to net contributions, which are the differences, for a given country, between contributions given to and received by the system (i.e., the last rows in the tables). In contrast to the traditional approach, our framework enables to evaluate how uncertainty shapes the nature of each market in giving or receiving shocks. Figures D1, D2, and D3 in online Appendix depict the net positions of each market given the nature and level of uncertainty. Several results emerge from these figures. First, the U.S. appear to be the main leader of the global financial system. This is especially true when looking at financial and macroeconomic uncertainty, as well as the U.S. EPU. The U.S. market's leading influence on others is however non-linear and varies according to the level of uncertainty. For instance, it decreases during periods of high financial uncertainty, macroeconomic uncertainty and Chinese economic policy uncertainty (by 102 p.p., 356 p.p. and 244 p.p., respectively) and increases during episodes characterized by high U.S. and European economic policy uncertainty (by 303 p.p. and 59 p.p., respectively). In other words, the role of the U.S. is reinforced during periods of European and American policy turmoil. Second, the U.K. also emerges as a second leader, especially during episodes of high European, U.S., and Chinese EPU, while most of the other countries (advanced and emerging) are clearly followers. Third, the role of China as a non-significant net contributor is also quite interesting since it runs counter to the common understanding that the domestic economic situation in China is likely to spill over to other markets. Its role during periods of increasing Chinese EPU appears to switch from a contributor in the low regime to a receiver in the high regime. Another interesting result is the changing role of Germany shifting from one position to the other depending on the regime. For instance, it switches from being a net contributor in the low regime to a net receiver in the high regime during periods of U.S. and European EPU, while it shifts from being a net receiver to neutral contributor in periods of macroeconomic uncertainty. Germany thus appears to be an international leader when uncertainty is low but loses this position when uncertainty is high.

6 Additional results

This section presents some robustness checks and additional results on the global bonds market and on Brexit-related issues.

6.1 Sensitivity analysis

6.1.1 Does forecasting horizon matter?

In the previous sections, we found that uncertainty is of crucial importance when evaluating financial markets networks since during periods of high uncertainty global network connectedness increases. Those results are obtained when decomposing the variance of forecasting errors at a specific horizon of $H = 5$ months. Here we check how the effect of uncertainty on financial interconnectedness evolves across various forecasting horizons H. We therefore compute our non-linear Diebold-Yilmaz spillover index for international equity markets in the high-uncertainty regime for various predictive horizons ranging from $H = 1$ to $H = 12$. Figure E1 in the online Appendix reports the global network connectedness for international equity markets in the high-uncertainty regime, for the 5 sources of uncertainty, for each considered horizon from 1 month to 12 months. It shows that results are quite robust to the predictive horizon. On average, the effect of uncertainty on network increases, peaks at 5 months, and then stabilizes at the same level.

6.1.2 Does VAR Cholesky ordering matter?

In order to estimate financial interconnectedness between equity markets returns, Diebold-Yilmaz's approach requires some identifying assumptions. As stressed in the empirical part of the paper, our preference goes to Cholesky factorization. However, this approach depends on the VAR-ordering specification. Table 8 performs robustness checks by computing max-min interval based on 100 randomly-selected VAR ordering of global interconnectedness index[28] in periods of low and high financial, macroeconomic and economic policy uncertainties. It shows that our results are robust since the range of global connectedness estimate across ordering is always lower than 9 p.p. However, as already pointed out in Section 5, when financial uncertainty is considered as transition variable some VAR-ordering specifications do not necessarily leads to an increase in connectedness.

6.2 Macroeconomic uncertainty and financial markets networks: a geographic perspective

The macroeconomic uncertainty measure considered so far in the paper is the one proposed by Jurado et al. (2015). This measure is well established and is available over a long sample but

[28] For a deterministic approach, see Klössner and Wagner (2013).

has the drawback of being only available for the U.S. economy. More recently, Scotti (2016) put forward macroeconomic uncertainty measures for a bunch of advanced economies (U.S., Europe, the U.K., Japan, and Canada), though the sample size is shorter (May 2003-December 2015). This section proposes to investigate the effect of those real-time macro-uncertainty measures on equity market networks. Table 9 reports global equity market spillovers in low- and high-uncertainty states with respect to the geographic area.[29] As before, financial markets connectedness increases in periods of high macro-uncertainty, especially in the presence of high uncertainty in Europe, the U.S. and Japan. Macroeconomic uncertainty in the U.K. and in Canada does not appear as a strong driver of equity markets connectedness. Figure F1 to F3 in the online Appendix complete our results by plotting the net contributions of each country with respect to the level of uncertainty and the geographic area. As in the previous section, contributions of each country in the system change depending on the uncertainty regime. Whatever geographic area is considered as generating macro uncertainty, the U.S. are always the main net contributor to the global system while other equity markets are net receivers or do not make significant contributions to the system. The role of the U.S. tends to be less important when moving into the high-uncertainty regime. While the contribution is more or less stable (approximately 350%) in periods of high macro-uncertainty in the U.K., it significantly decreases by approximately 200 p.p. in times of uncertainty in the U.S. and Europe (from 445% to 244% for the former and from 428% to 250% for the latter), and by more than 350 p.p. in times of uncertainty in Japan (from 469% to 94%). This behavior is less pronounced during periods of macro-uncertainty in Canada, where the U.S. contribution to net uncertainty decreases by approximately 90 p.p. when moving from the low to the high regime.

6.3 Results on the global bonds market

As a robustness check of the effect of uncertainty on network connectedness, we also apply our model to government bond markets for the overall sample (except Brazil) over the period from April 2004 to December 2015. Results are presented in the Table 10. We note that those results are qualitatively similar to those for equity markets, meaning that global interconnectedness on the bond market increases with respect to uncertainty. It is noteworthy that the increase in connectedness is stronger than for equity markets and that interestingly the eco-

[29]To save space, we do not report detailed pairwise connections; those results are available from the authors upon request.

nomic policy uncertainty in China appears to be the most important driver of this upward shift in connectedness.

6.4 Impact of Brexit-related uncertainty on European markets

While it is always difficult to capture the effect of uncertainty on economic and financial interconnectedness, a recent event in the United Kingdom provides an interesting case study for a discussion of Brexit-related uncertainty and potential consequences for European countries. Recall the facts of the case: on Thursday, 23 June, the United Kingdom voted in favor of Brexit, with the consequence that the country would leave the European Union, leading to possible important economic disruptions. Together with market fluctuations, uncertainty in UK also increased significantly over the period, as the Economic Policy Uncertainty index of Baker et al. (2016) shows in Figure H1 in the online Appendix.[30] This section is attempt to evaluate the effect of Brexit-related uncertainty on European equity markets interconnectedness. Our investigation focuses only on core and periphery European markets (i.e. the United Kingdom, France, Germany, Italy, the Netherlands, Spain, Portugal, and Greece). As a neutral point of comparison, we consider two different sample periods: from January 2000 to June 2016, which includes a sharp increase in uncertainty related to the Brexit period, and from January 2000 to August 2015, which does not capture recent events related to Brexit.[31] We consider our non-linear two-regime approach presented in this paper; a test significantly rejects the null of linearity. Figure 1 presents the interconnectedness of European markets depending on U.K. EPU, for various forecast horizons (from $H = 1$ to $H = 12$). It compares the degree of interconnectedness estimated over the non-Brexit period (blue bars, from Jan. 2000 to Aug. 2015) with the one estimated over the period that includes the Brexit (red bars, from Jan. 2000 to Jun. 2016). This result shows that when including the recent Brexit period, the effect of U.K. EPU on equity market connectedness is about twice meaning that the recent period of uncertainty is of primary importance in terms of network reactions among European equity markets.

[30] The Brexit-related uncertainty index is constructed by scaling the UK EPU index by the share of EPU articles that also contain "Brexit", "EU" or "European Union". It can be freely download at http://www.policyuncertainty.com/brexit.html.

[31] While the selection of sub-sample periods could be considered subjective, this choice was been made by comparing the evolution of UK EPU and Brexit-related uncertainty, which were both at a low in August 2015.

7 Conclusions

In this paper, we assess financial interconnectedness among 13 stock markets (including developed and emerging countries) by allowing for non-linear effects in the spillover index approach developed by Diebold and Yilmaz (2009). In this respect, we put forward a non-linear Threshold VAR model whose regimes depend on the level of various uncertainty measures. Our main result is that the global equity market is much more connected during periods of high uncertainty than during periods of low uncertainty. Empirical results are robust to the choice of uncertainty measures (economic, political or macroeconomic uncertainty). We also find that the United States are the main source of connectedness within the global equity system, as well as the United Kingdom but to a lesser extent. All other countries tend to act as net receivers of financial spillovers. Those findings are among the first to empirically support the idea that uncertainty can be a channel of contagion on financial markets. Robustness checks show that this result also holds on the global bond market. At the light of current economic and political conditions, this result has strong potential implications. Indeed, according to the current high degree of economic policy uncertainty, leading thus to a stronger interdependence within the global equity market, a negative financial shock is likely to spread over the rest of the world creating hence a global turmoil. This potential threat should be accounted for by public authorities in charge of financial stability. Such a goal requires a real-time monitoring of the many uncertainty indicators in order to accurately assess the degree of uncertainty. Still, the policies required to reach such an objective are far from being obvious and concern policy actions (monetary, fiscal, international cooperation), but also regulation. No doubt that this topic will fuel up future research works.

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Table 1: Diebold-Yilmaz network index for global equity markets

	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	75.3	1.9	5.4	0.8	0.4	2.2	0.3	1.2	3.9	1.4	1.7	3.5	2.0	25*
UK	56.3	24.8	3.3	0.5	1.2	0.7	0.3	1.2	5.0	3.1	0.8	1.9	1.0	75*
GER	54.1	6.3	24.4	1.6	0.2	1.5	0.1	0.4	2.6	2.3	0.1	4.1	2.3	76*
FRA	54.6	12.0	11.5	9.3	0.9	0.3	0.6	0.7	2.4	3.2	0.4	2.8	1.5	91*
ITA	40.7	13.9	13.3	8.4	11.7	0.3	1.0	1.2	4.2	1.1	0.6	1.2	2.4	88*
NLD	53.0	13.2	8.5	3.6	0.3	10.5	0.2	0.5	2.6	3.6	0.6	1.4	2.0	90*
SPA	43.8	13.8	6.5	8.5	3.6	0.4	13.7	1.1	4.2	2.0	0.4	1.1	1.0	86*
PRT	30.2	17.9	7.5	11.5	3.8	0.1	3.5	18.1	2.2	1.8	1.6	1.7	0.4	82*
GRC	25.2	14.1	6.5	6.4	2.4	1.4	4.3	2.9	29.7	2.4	0.8	1.3	2.0	70*
CHN	8.6	3.4	2.2	1.3	0.7	0.2	0.6	3.5	2.9	70.3	1.0	1.8	3.4	30*
BRA	35.8	7.0	1.9	1.0	1.3	4.2	0.9	0.3	5.0	2.5	36.7	0.4	3.0	63*
RUS	26.1	6.1	1.3	2.7	0.8	2.9	1.5	0.6	5.1	1.6	7.3	39.5	4.4	61*
IND	24.1	5.0	2.2	2.5	5.0	1.1	1.7	2.2	3.3	1.5	1.5	1.9	47.4	52*
TO	453*	115*	70*	49*	21*	15*	15*	16*	43	26*	17*	23*	25*	68.3%*
NET	428*	34*	-6*	-42*	-68*	-74*	-71*	-66*	-27	-3	-46*	-38*	-27*	

Notes: The table depicts Diebold-Yilmaz interconnectedness measure for international equity markets over a predictive horizon of 5 months. The "FROM" column gives row sums (from all others to j); the "TO" row gives the column sums (to all others from j); and the "NET" row gives the difference between "TO" and "FROM". The botton-right value is the percent of forecast error variance coming from interconnectedness. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 2: Tests for the threshold effect in global equity markets

Threshold variables	Threshold value	Wald Statistics			% high uncertainty	Average duration (in months)
		Sup-Wald	Avg-Wald	Exp-Wald		
VXO	22.375	773.77*	605.34*	382.27*	41.01%	6.4
M1	0.714	847.45*	678.49*	419.11*	19.36%	7.3
EPU US	104.89	576.77*	500.09*	283.77*	49.77%	7.4
EPU Europe	138.42	779.95*	592.92*	385.36*	39.17%	5.5
EPU China	150.27	609.85*	514.33*	300.35*	23.50%	3.5

Notes: VXO is the CBOE index of percentage implied volatility used to proxy for financial uncertainty. M1 denotes macroeconomic uncertainty at 1 month according to Jurado et al. (2015). EPU indexes are policy uncertainty measures developed by Baker et al. (2016). Sup-Wald: maximum Wald statistic over all possible threshold values, avg-Wald: average Wald statistic over all possible values, exp-Wald: function of the sum of exponential Wald statistics. * denotes the rejection of the null hypothesis at the 5% significance level.

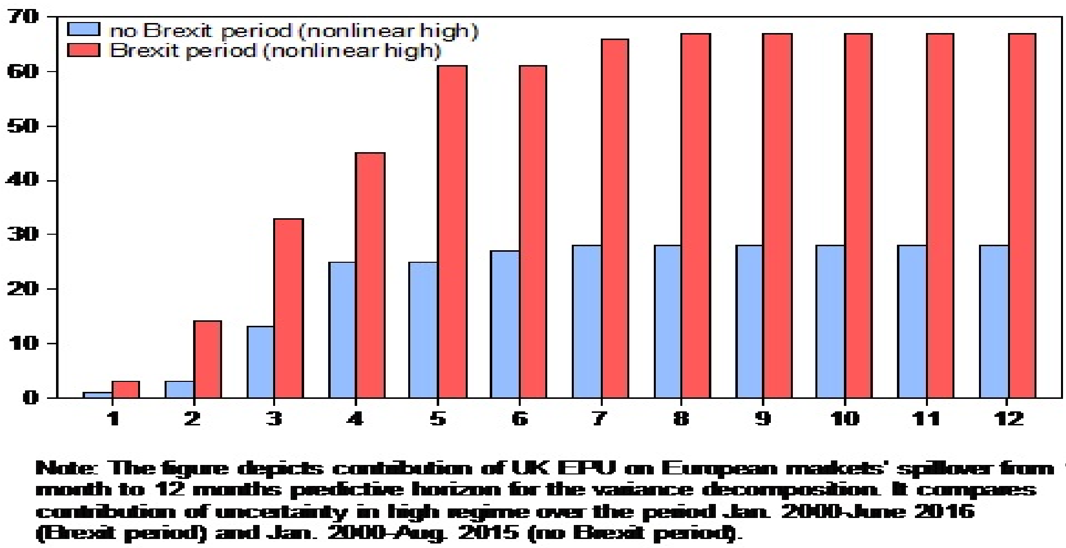

Figure 1: Does Brexit-related uncertainty affect European equity market interconnectedness?

Note: The figure depicts the interconnectedness of European markets depending on UK EPU, for various forecast horizons (from $H = 1$ to $H = 12$). It compares the degree of interconnectedness estimated over the non-Brexit period (blue bars, from Jan. 2000 to Aug. 2015) with the one estimated over the period that includes the Brexit (red bars, from Jan. 2000 to Jun. 2016).

Table 3: Nonlinear Diebold-Yilmaz network index in global equity markets under financial uncertainty

	low uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	70.7	0.9	8.6	4.5	2.2	1.9	1.4	1.5	0.4	4.3	2.3	0.8	0.4	29*
UK	53.3	23.5	5.2	1.9	2.3	1.9	0.5	1.9	1.2	4.6	2.5	0.4	0.9	77*
GER	50.5	5.2	21.3	4.4	2.1	2.5	2.8	1.4	1.1	3.4	5.1	0.1	0.2	79*
FRA	50.1	9.6	12.1	10.6	1.0	1.7	0.9	2.0	1.5	5.1	4.7	0.4	0.4	89*
ITA	39.8	11.8	13.6	10.2	12.6	1.3	0.8	2.1	1.0	3.3	3.2	0.2	0.2	87*
NLD	50.9	12.3	9.0	3.5	1.7	9.8	1.0	2.6	1.7	3.8	3.3	0.3	0.1	90*
SPA	46.4	11.6	6.8	7.4	5.2	0.3	15.6	0.6	0.6	1.7	2.6	0.8	0.5	84*
PRT	29.3	13.2	9.0	11.3	2.6	1.8	2.0	18.2	1.1	1.6	5.4	1.6	2.7	82*
GRC	26.5	11.3	7.8	8.9	2.5	1.5	4.3	2.1	31.3	0.7	1.1	0.5	1.8	69*
CHN	5.9	3.8	4.3	3.1	2.2	1.2	1.1	4.6	3.9	64.4	3.2	0.5	1.8	36*
BRA	34.8	7.3	2.8	2.9	2.4	1.5	2.6	1.5	1.8	3.8	37.1	0.5	0.9	63*
RUS	24.3	4.5	0.9	1.7	3.5	3.5	1.9	1.5	3.2	2.3	12.1	38.7	2.0	61*
IND	20.2	2.4	6.1	7.1	5.4	4.0	1.9	2.5	4.2	3.6	3.4	0.3	38.8	61*
TO	432*	94*	86*	67*	33*	23*	21*	24*	22*	38*	49*	6	12*	69.8% (68.7−72.6)
NET	403*	17*	7	-22*	-54*	-67*	-63*	-57*	-47*	2	-14*	-55*	-49*	

	high uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	58.8	2.9	3.0	3.2	6.5	1.9	1.5	6.5	1.5	6.0	2.8	1.7	3.8	41*
UK	41.2	19.2	6.1	1.5	5.0	1.5	3.9	5.0	1.7	6.3	0.6	3.6	4.4	81*
GER	39.4	6.5	17.8	4.3	4.2	2.1	2.5	4.0	1.5	4.8	3.5	5.1	4.3	82*
FRA	39.1	9.3	12.5	10.0	2.6	1.5	2.6	3.8	1.5	5.2	3.0	4.2	4.6	90*
ITA	29.6	9.8	11.1	9.2	9.6	2.1	2.5	4.3	1.4	3.7	1.5	5.2	10.0	90*
NLD	38.1	11.3	9.2	3.1	3.2	7.7	2.9	4.3	2.5	6.7	1.2	4.7	5.3	92*
SPA	33.2	10.8	8.1	6.4	6.8	2.0	11.4	8.6	2.1	2.4	2.3	1.5	4.4	89*
PRT	26.9	15.6	10.2	11.4	2.7	2.4	4.1	16.4	2.0	2.7	2.1	1.1	2.4	84*
GRC	21.4	10.2	5.0	7.2	6.1	2.2	3.8	5.1	26.0	2.3	3.2	4.7	2.8	74*
CHN	5.3	8.3	4.2	1.7	4.0	0.5	8.1	1.8	1.3	62.1	1.2	0.8	0.6	38*
BRA	27.0	9.2	4.3	2.9	4.8	4.0	5.6	5.0	1.3	3.6	26.1	2.2	4.0	74*
RUS	21.1	5.2	2.3	0.6	3.4	5.1	7.3	1.5	2.8	6.2	6.7	31.9	6.1	68*
IND	20.0	6.3	2.5	2.1	4.1	0.7	3.5	3.7	2.8	5.5	7.2	2.1	39.5	61*
TO	342*	105*	79*	53*	53*	26*	48*	54*	22*	55*	35*	37*	53*	74.1% (71.2−76.2)
NET	301*	25	-4	-37	-37*	-66*	-40*	-30*	-52*	17	-31	-31	-8	

Notes: The table depicts nonlinear interconnectedness measure in the low- and high-financial-uncertainty regimes for international equity markets over a predictive horizon of 5 months. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 4: Nonlinear Diebold-Yilmaz network index in international equity markets under macroeconomic uncertainty

	low uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	74.6	1.9	2.1	1.1	8.2	2.2	0.3	2.5	0.6	3.5	1.2	1.2	0.6	25*
UK	61.1	25.9	1.0	1.4	4.1	0.6	0.8	1.4	0.3	1.1	0.4	0.7	1.2	74*
GER	56.5	6.6	19.6	0.9	3.4	2.1	1.3	0.6	0.7	1.8	2.8	2.6	1.1	80*
FRA	59.8	10.6	8.9	7.9	3.9	0.5	0.5	0.2	0.3	1.9	0.9	2.2	2.6	92*
ITA	48.0	12.4	9.2	7.8	15.2	0.7	0.5	0.4	1.2	1.9	0.4	1.1	1.1	85*
NLD	56.2	12.6	6.5	2.5	4.4	9.5	0.9	0.3	1.0	1.9	0.5	1.6	2.2	91*
SPA	45.2	12.3	7.2	5.1	5.8	0.9	11.1	1.3	2.3	3.7	0.7	1.2	3.0	89*
PRT	35.7	15.1	8.3	9.4	3.9	0.4	2.0	16.2	1.5	0.9	0.8	2.9	2.9	84*
GRC	28.0	12.3	3.8	5.9	5.1	1.1	3.9	2.7	28.5	0.8	1.1	1.6	5.1	71*
CHN	6.8	2.6	3.3	2.6	1.8	1.0	1.8	2.2	2.4	72.4	1.6	0.5	0.8	28*
BRA	35.3	7.9	3.9	0.4	1.4	3.0	1.1	0.7	7.6	2.5	34.1	0.2	1.9	66*
RUS	28.1	3.7	2.6	1.8	2.8	3.5	1.2	1.1	7.1	3.4	6.5	34.6	3.5	65*
IND	26.1	8.2	1.9	0.3	5.5	1.1	2.1	2.6	2.1	2.2	1.8	0.4	45.6	54*
TO	487*	106*	59*	39*	50*	17*	16*	16*	27*	26*	19*	16*	26*	69.6% (67.4−70.7)
NET	462*	32*	-22*	-53*	-34*	-74*	-73*	-68*	-44*	-2	-49*	-49*	-28*	

	high uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	27.8	2.1	8.6	8.1	5.0	5.5	5.4	7.0	9.9	2.3	7.0	1.6	9.7	72*
UK	16.3	6.4	7.6	10.4	3.6	1.1	6.5	10.3	8.2	8.5	5.4	0.6	15.1	94*
GER	22.3	3.8	16.6	7.5	3.4	4.2	5.5	7.0	7.8	2.8	4.6	2.7	11.9	83*
FRA	17.2	5.8	9.7	12.5	2.1	2.1	6.9	13.0	4.7	8.6	2.3	1.9	13.0	88*
ITA	16.8	9.2	12.0	6.7	7.4	3.0	4.8	8.0	3.6	9.4	2.6	2.2	14.3	93*
NLD	20.0	6.2	8.4	5.9	1.4	4.8	8.3	7.4	5.9	7.8	2.8	1.7	19.6	95*
SPA	12.0	6.6	7.6	9.9	4.7	6.6	9.5	11.1	5.6	9.1	2.2	1.7	13.3	90*
PRT	11.7	7.6	7.3	12.0	4.7	5.1	6.1	19.6	3.1	8.9	4.6	1.9	7.7	80*
GRC	12.8	6.4	9.9	5.5	2.7	3.3	4.7	2.9	12.6	11.3	7.2	1.2	19.3	87*
CHN	7.1	5.1	5.8	11.5	5.3	4.8	2.5	2.8	5.5	28.1	10.7	2.3	8.5	72*
BRA	18.3	3.1	4.5	9.2	7.4	8.4	6.4	5.6	5.3	4.0	13.1	1.6	13.1	87*
RUS	13.7	5.5	7.7	7.5	4.6	5.3	8.3	3.8	8.0	0.7	3.2	14.0	17.8	86*
IND	10.3	4.5	1.7	1.2	5.5	5.1	10.3	5.7	2.9	11.3	4.2	1.6	35.7	64
TO	179*	66*	91*	95*	50*	54*	76*	84*	70*	85*	57*	21	163	84.0% (81.1−87.4)
NET	106*	-27*	8	8	-42*	-41*	-15	4	-17	13	-89*	-65*	99	

Notes: The table depicts nonlinear interconnectedness measure in the low- and high-macroeconomic-uncertainty regimes for international equity markets over a predictive horizon of 5 months. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 5: Nonlinear Diebold-Yilmaz network index in international equity markets under U.S. economic policy uncertainty

	low uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	81.9	2.3	0.7	1.5	2.5	1.0	0.6	2.1	1.1	0.5	0.3	4.5	1.0	28*
UK	45.0	38.3	1.1	2.2	1.0	1.4	0.5	2.4	2.3	0.2	0.6	3.1	1.8	63*
GER	46.7	6.4	29.1	1.6	2.5	0.6	0.9	0.9	1.2	0.2	1.4	7.0	1.5	65*
FRA	48.5	12.3	12.8	13.1	1.5	1.1	0.7	0.8	0.8	0.2	0.4	6.8	1.1	83*
ITA	25.7	12.7	14.7	9.9	23.7	0.2	1.0	1.7	3.4	1.4	1.4	3.7	0.5	80*
NLD	41.4	15.8	13.2	4.7	3.0	13.9	0.3	0.4	0.8	0.1	0.8	4.7	1.1	89*
SPA	35.5	10.8	8.0	5.4	5.7	0.7	22.9	1.4	2.1	0.3	1.0	3.5	2.8	77*
PRT	21.3	11.5	9.3	17.2	4.2	0.5	4.8	22.1	2.3	0.2	0.5	4.1	2.0	75*
GRC	11.3	9.4	3.8	12.8	0.4	1.1	5.6	1.7	43.4	3.2	2.0	0.8	4.4	55*
CHN	6.6	0.5	1.3	1.9	1.1	1.5	0.5	1.0	3.3	78.5	1.8	0.3	1.8	34*
BRA	27.8	7.6	3.1	0.6	2.4	1.1	4.3	2.3	5.2	2.1	40.4	0.5	2.7	58*
RUS	21.1	2.5	3.7	0.7	2.1	4.3	1.9	1.8	6.4	2.0	9.0	40.0	4.3	63*
IND	21.7	3.0	0.6	1.3	4.7	0.8	0.3	1.8	0.9	2.5	2.9	1.6	57.9	62*
TO	240*	114*	113*	96*	26*	18*	47*	27*	42*	23*	35*	29*	22*	64.0% (62.5–70.5)
NET	212*	51*	48*	13*	-54*	-71*	-30*	-48*	-13	-11	-23	-34*	-40	

	high uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	48.4	8.9	6.5	1.8	0.6	3.3	6.2	4.4	2.0	4.6	2.7	6.7	3.6	31*
UK	38.0	17.2	7.2	1.5	1.7	1.5	3.6	3.1	3.1	3.7	3.1	9.8	6.5	81*
GER	48.7	5.5	16.8	0.7	0.5	43.8	3.2	4.4	3.3	1.5	1.9	5.9	3.7	81*
FRA	46.6	9.1	8.8	5.7	0.8	2.0	3.9	3.6	4.2	1.7	1.9	6.2	5.5	93*
ITA	34.2	7.8	11.2	6.7	5.5	3.3	4.7	3.0	6.0	1.1	2.2	7.0	7.4	91*
NLD	41.0	11.0	9.2	0.9	1.3	7.8	2.8	2.7	3.4	2.6	1.9	7.5	8.1	90*
SPA	35.7	9.0	5.5	6.7	3.7	3.1	11.4	2.9	5.4	1.3	2.7	6.5	6.0	90*
PRT	31.8	13.3	5.9	3.5	2.6	1.1	7.9	10.2	5.3	3.1	2.9	4.9	7.5	89*
GRC	29.3	9.9	6.5	4.2	4.8	1.2	6.0	3.1	15.2	1.6	2.1	6.6	9.7	81*
CHN	10.6	9.4	7.1	2.2	3.7	2.0	13.3	2.9	2.5	34.2	5.4	1.6	5.1	35*
BRA	28.9	3.9	5.6	2.6	2.0	33.4	13.1	1.6	1.7	5.1	13.0	10.0	9.1	75*
RUS	18.1	11.9	2.7	1.5	4.0	2.3	10.1	1.1	5.5	2.9	6.2	25.2	8.4	70*
IND	12.5	8.7	7.5	1.1	7.1	3.6	4.9	1.1	5.2	3.8	4.3	9.8	30.4	70*
TO	546*	97*	73*	40*	24*	30*	25*	13*	18*	52*	30*	13*	13	75.0% (72.0–78.0)
NET	515*	16*	-8*	-53*	-67*	-60*	-65*	-76*	-63*	17	-45	-57*	-57	

Notes: The table depicts nonlinear interconnectedness measure in the low- and high-U.S.-economic-policy-uncertainty regimes for international equity markets over a predictive horizon of 5 months. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 6: Nonlinear Diebold-Yilmaz network index in international equity markets under European economic policy uncertainty

	low uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	80.8	0.7	2.1	2.9	1.0	2.2	2.8	1.9	0.3	0.5	0.2	3.8	0.9	19*
UK	44.7	34.8	2.1	3.9	1.7	1.9	1.5	3.1	0.5	0.8	0.6	3.1	1.3	65*
GER	45.5	6.7	30.0	3.3	0.3	0.5	2.7	1.6	0.2	0.4	1.3	6.4	1.0	70*
FRA	46.4	10.2	17.5	13.0	0.2	1.0	1.5	0.9	0.1	0.7	0.1	8.1	0.5	87*
ITA	29.3	12.8	21.4	9.0	19.9	0.0	0.8	1.5	1.0	0.2	1.0	2.7	0.5	80*
NLD	39.1	15.6	14.8	5.0	0.9	14.0	0.6	0.8	0.1	0.3	0.9	6.6	1.2	86*
SPA	35.0	12.5	11.3	4.9	3.6	0.4	23.3	2.0	0.3	0.4	0.7	4.3	1.3	77*
PRT	20.1	7.6	15.6	15.4	3.4	1.5	6.0	21.4	1.4	0.8	0.5	5.5	0.9	79*
GRC	13.7	6.6	9.3	8.5	0.4	1.5	7.8	1.6	41.9	1.7	2.8	1.5	2.7	58*
CHN	9.3	0.4	1.6	1.2	1.5	0.8	0.3	3.4	0.7	76.5	1.6	1.2	1.3	23*
BRA	32.5	8.6	2.6	0.7	1.9	1.0	3.8	1.2	4.5	2.4	35.6	0.7	4.4	64*
RUS	25.8	2.6	2.5	1.9	1.7	5.4	3.9	2.7	4.2	2.1	6.7	36.2	4.3	64*
IND	28.4	5.1	1.6	2.4	4.1	2.4	1.2	5.9	0.8	2.0	2.6	2.6	40.7	59*
TO	370*	89*	102*	59*	21*	19*	33*	27*	14*	12*	19*	47*	20*	64.0% (60.6−71.0)
NET	351*	24*	32*	-28*	-59*	-67*	-44*	-52*	-44*	-11	-45	-17*	-39	

	high uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	60.4	7.7	6.0	0.4	2.0	0.6	3.8	0.6	1.0	7.6	3.1	4.8	2.1	40*
UK	54.1	14.7	5.9	1.4	1.1	0.3	2.0	1.1	0.6	6.2	3.0	6.0	3.5	85*
GER	53.9	6.8	17.4	0.8	0.9	1.4	3.1	1.4	0.5	4.3	2.1	4.1	3.3	83*
FRA	50.2	12.0	8.4	6.1	0.6	0.3	4.4	1.6	1.2	3.7	1.7	5.0	4.9	94*
ITA	41.5	11.8	7.8	7.4	8.3	0.9	4.7	1.5	1.8	2.1	1.4	5.2	5.5	92*
NLD	44.8	9.6	8.1	2.4	1.3	5.1	4.0	1.8	1.4	7.1	2.9	6.3	5.1	95*
SPA	46.0	9.6	4.8	7.5	2.4	0.5	11.3	1.2	2.9	1.7	2.0	4.6	5.5	89*
PRT	36.2	17.4	4.7	4.3	2.8	1.0	5.7	10.2	2.4	3.2	0.9	6.2	4.9	90*
GRC	32.8	12.5	5.5	4.7	5.3	1.0	4.2	1.5	14.1	2.8	1.0	7.8	6.7	86*
CHN	9.6	3.3	5.0	1.5	4.2	1.8	4.3	1.6	2.5	55.7	0.2	6.0	4.5	44*
BRA	33.3	7.0	2.5	0.7	2.2	4.1	7.5	0.8	1.9	1.8	24.5	7.0	6.7	75*
RUS	23.1	23.4	4.2	0.4	2.3	1.8	2.9	0.9	3.0	4.0	4.5	28.7	0.7	71*
IND	24.5	6.6	5.2	0.7	6.5	3.9	2.3	0.4	0.3	6.7	2.3	7.8	32.9	67*
TO	450*	128*	68*	32*	31*	18*	49*	14*	20*	52*	25*	71*	53*	77.7% (74.3−80.0)
NET	410*	43*	-15*	-62*	-61*	-47*	-40*	-76*	-66*	8	-50	0	-11	

Notes: The table depicts nonlinear interconnectedness measure in the low- and high-European-economic-policy-uncertainty regimes for international equity markets over a predictive horizon of 5 months. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 7: Nonlinear Diebold-Yilmaz network index in international equity markets under Chinese economic policy uncertainty

	low uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	68.6	4.5	3.9	0.3	1.2	1.3	0.9	1.2	3.2	8.3	1.8	1.3	3.6	31*
UK	48.5	24.6	5.4	0.2	1.8	1.3	0.9	2.6	4.8	6.3	0.5	0.9	2.4	75*
GER	48.5	11.1	19.4	0.1	1.9	0.4	0.1	2.4	1.7	6.1	2.6	3.3	2.4	81*
FRA	50.9	13.6	9.8	7.5	1.3	0.2	0.5	2.0	4.1	4.7	1.5	2.2	1.7	92*
ITA	40.1	14.3	10.9	7.6	14.5	0.4	0.3	1.2	3.5	2.4	1.5	2.3	1.1	86*
NLD	50.5	15.6	8.3	2.1	2.4	9.4	13.5	2.1	2.9	4.6	0.5	1.0	0.4	91*
SPA	39.9	14.6	7.1	6.0	3.8	0.1	2.2	2.5	4.6	3.2	1.0	1.6	2.1	87*
PRT	26.6	18.4	9.5	10.4	3.7	0.6	4.0	18.2	3.8	1.6	1.5	1.1	2.3	82*
GRC	23.0	14.9	5.9	6.7	2.5	0.2	1.8	3.9	33.2	4.0	0.5	0.8	0.5	67*
CHN	7.2	5.8	8.0	0.2	1.4	0.8	0.1	2.0	1.2	70.6	0.2	0.2	0.6	29*
BRA	33.8	11.5	2.2	2.2	2.3	2.0	2.0	1.7	1.9	2.3	34.4	0.1	3.8	66*
RUS	22.5	7.2	1.3	3.0	2.4	1.1	1.5	1.3	1.0	4.4	6.4	38.7	9.2	61*
IND	20.6	12.4	1.9	1.0	7.4	1.2	0.6	2.5	7.8	3.0	2.1	1.0	38.7	61*
TO	412*	144*	74*	40*	32*	10	15*	25*	40	51*	20*	16*	30*	69.9% (67.6−71.0)
NET	381*	68*	-6	-53*	-54*	-81	-72*	-57*	-26	22*	-45*	-46*	-31*	

	high uncertainty													
	USA	UK	GER	FRA	ITA	NLD	SPA	PRT	GRC	CHN	BRA	RUS	IND	FROM
USA	23.7	8.4	10.6	4.6	9.0	2.8	16.0	5.1	3.2	1.8	2.1	6.0	6.7	76*
UK	23.0	12.2	6.9	8.0	8.2	3.1	16.1	3.3	3.3	4.4	2.4	5.1	4.0	88*
GER	26.1	3.7	13.4	4.0	6.4	4.4	7.9	9.9	1.6	5.0	0.9	11.4	5.3	87*
FRA	20.1	7.3	8.2	9.5	7.8	4.5	14.3	8.3	3.4	3.9	0.9	8.7	3.2	90*
ITA	17.2	10.0	7.3	9.8	10.7	4.0	12.0	12.2	1.6	1.9	0.3	10.6	2.4	89*
NLD	22.8	9.0	6.5	6.8	6.4	10.7	11.7	7.0	1.8	5.0	2.1	7.6	2.7	89*
SPA	15.6	11.9	6.2	10.3	9.7	3.2	17.4	7.1	1.9	2.0	2.0	7.7	5.1	83*
PRT	15.7	9.1	7.2	9.9	5.7	5.3	6.3	24.8	1.0	1.2	0.4	7.5	5.7	75*
GRC	16.2	12.0	10.6	4.2	2.9	2.0	10.0	13.6	11.3	0.1	2.5	11.8	2.6	89*
CHN	11.4	10.6	3.9	1.2	14.3	7.8	5.3	2.4	5.8	18.4	7.7	4.9	6.5	82*
BRA	16.6	14.3	7.8	2.4	4.1	4.6	10.9	5.8	3.1	2.7	13.8	4.5	9.4	86*
RUS	15.2	8.7	5.0	3.9	5.1	13.3	1.6	2.1	1.2	8.2	5.6	25.6	4.6	74*
IND	13.2	7.1	7.2	2.1	9.5	2.4	5.5	3.9	3.9	2.8	4.6	7.8	30.1	70*
TO	213*	112*	87*	67*	89*	57*	118	81*	32*	39*	32*	94*	58*	83.0% (78.1−85.0)
NET	137*	24*	1	-23*	-1	-32	35	5	-57*	-42*	-55	19	-12	

Notes: The table depicts nonlinear interconnectedness in the low- and high-Chinese-economic-policy-uncertainty regimes for international equity markets over a predictive horizon of 5 months. * denotes rejection of the null hypothesis at the 5% significance level computed using a parametric bootstrap procedure (10,000 replications).

Table 8: Global equity market interconnectedness and uncertainty: the effect of model specification

Uncertainty source	Low uncertainty	High uncertainty
Financial uncertainty	69.8% (67.7−74.0)	74.1% (70.1−77.1)
Macro uncertainty	69.6% (66.9−71.5)	84.0% (80.2−89.1)
EPU US	64.0% (60.1−70.9)	75.0% (72.1−79.9)
EPU Europe	64.0% (60.1−70.4)	77.7% (74.3−79.2)
EPU China	69.9% (67.2−72.1)	83.0% (78.1−85.4)

Notes: The table summarizes global interconnectedness in the low- and high-uncertainty regimes with respect to the source of uncertainty. Models are computed over 10,000 parametric bootstrap replications. Between parenthesis are minimum and maximum spillover interval based on 100 randomly selected VAR orderings.

Table 9: Global equity market interconnectedness in times of macroeconomic uncertainty: a geographic perspective

Geographic area	Low uncertainty	High uncertainty
U.S.	75.3%*	82.6%*
Europe	75.7%*	80.4%*
UK	78.4%*	79.9%*
Japan	76.1%*	86.5%*
Canada	77.6%*	79.5%*

Notes: The table summarizes global interconnectedness measure in the low- and high-uncertainty regimes with respect to geographic area. Models are computed over 10,000 parametric bootstrap replications and 100 randomly selected VAR orderings. * denotes that interconnectedness are significant at the 5% level and robust to randomly selected VAR orderings.

Table 10: Global government bond yields interconnectedness in times of uncertainty

Uncertainty source	Low uncertainty	High uncertainty
Financial uncertainty	65.1%*	78.6%*
Macro uncertainty	66.9%*	75.1%*
EPU US	64.8%*	72.8%*
EPU Europe	63.6%*	87.6%*
EPU China	63.2%*	89.4%*

Note: The table summarizes global government bonds interconnectedness in the low- and high-uncertainty regimes with respect to uncertainty. Models are computed over 10,000 parametric bootstrap replications. * denotes that interconnectedness are significant at the 5% level.