Relation between regional uncertainty spillovers in the global banking system

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Abstract

We report on time-varying network connectedness within three banking systems: North America (NA), the European Union (EU), and Southeast Asia (ASEAN). The original method by Diebold and Yilmaz is improved by using exponentially weighted daily returns and ridge regularization on vector autoregression (VAR) and forecast error variance decomposition (FEVD). We compute the total network connectedness for each of the three banking systems, which quantifies regional uncertainty. Results over rolling windows of 300 days during the period from January 2005 to October 2015 reveal changing uncertainty patterns which are similar across regions, with common peaks associated with identifiable exogenous events. Lead-lag relationships among changes of total network connectedness of the three systems, quantified by transfer entropy, reveal that uncertainties in the three regional systems are significantly causally related, with the NA system having the largest influence on EU and ASEAN.

Keyworkds: Systemic risk; forecast error variance decomposition; connectedness; spillover effects.

I. Introduction

Financial markets are increasingly becoming more interconnected (Moghadam and Vinals, 2010), and shocks initially affecting one part of the system can quickly propagate to the rest of it. Therefore, understanding the patterns of distress propagation within financial markets is important to characterize systemic risk. After the Global Financial Crisis of 2007-2009, significant effort has been devoted into understanding the mechanics of distress propagation within banking systems. On one hand, a strand of literature focused on modeling the processes through which contagion may occur in interbank networks (see for instance Glasserman and Young (2016); Caccioli et al. (2018) for recent reviews). On the other hand, another strand of literature focused on the quantification of systemic risk from market data (see Adrian and Brunnermeier (2016); Brownlees and Engle (2016)). In particular, Diebold and Yilmaz (2009) proposed a method based on Forecast Error Variance Decomposition (FEVD) to estimate from market data networks of interdependencies between firms, and they used the connectedness of the estimated networks to quantify spillovers of uncertainty between variables.

In this paper, we use the methodology of the aforementioned work by Diebold and Yilmaz (2009) to estimate the time evolution of connectedness in three regional banking systems: North America (NA), Southeast Asia (ASEAN), and the European Union (EU). Through VAR and FEVD, we compute the pairwise connectedness between pairs of banks in each region, and we aggregate such pairwise connectedness to compute a measure of total connectedness for the region.

The time-varying total connectedness computed for each banking system, from a 300 days rolling window during the period from January 2005 to October 2015, indicates temporal changes of systemic risk, with peaks during major crisis events and troughs during normal periods. Analogous results have been observed in other financial systems and different regions (Diebold and Yilmaz, 2009, 2012, 2014; Chau and Deesomsak, 2014; Alter and Beyer, 2014; Fengler and Gisler, 2015; Demirer et al., 2015). It has to be stressed that, unlike Diebold and Yilmaz (2009) who view all financial institutions as belonging to one global system, here we group banks into three regional banking systems. In this way we can perform a comparative analysis between the different regions, which allows us to highlight similarities and differences between them. Furthermore, this allow us to quantify the existence of causal relations between different regions. We must note that combining all the banks together could be somehow misleading because the banks' equities in the three banking systems trade in different stock markets which have significantly different trading hours.

The main results of our analysis are as follows: First, we notice that the structure of the peaks in the three regional banking systems is very similar with large peaks associated to significant, identifiable major events. Although the overall patterns are similar, we observe two important differences between the systems. The first is the fact that the overall scale of connectedness is different, with the North-American banking system being more interconnected than the EU, and this being in turn more interconnected than the Southeast Asian system. Second, we uncover the existence of lead-lagged relations between the different time series. To quantify this effect, we compute the transfer entropy between the time series associated with changes of connectedness in the different regions, and we uncover the existence of significant net information flows from North America to the EU, from North-America to Southeast Asia, and from the EU to Southeast Asia. The robustness of our finding is tested by using different measures for transfer entropy. In particular we find consistent results for the net information flow both with a linear measure of transfer entropy (which corresponds to a Granger causality analysis) as well as with non-linear measures with different parameters. We also retrieve similar causal relation for both one day and five days returns. To the best of our knowledge, this causality study between regional uncertainties is the first of its kind.

The rest of this paper is organized as follows. In Section II we present a literature review and place our paper within the context of previous works. In Section III we describe the used data, while Section IV provides a brief description of our methodology. Section V illustrates and discusses the main results of the paper, and finally we present our conclusions in Section VI.

II. Literature review

The literature on systemic risk and contagion in the banking network can be broadly classified into two categories. The first category comprises network models which aim to describe various causal mechanics of financial contagion, which can be calibrated with balance-sheet data (Furfine, 2003; Degryse and Nguyen, 2007; Upper and Worms, 2004; Müller, 2006; Cont et al., 2010; Upper, 2011; Birch and Aste, 2014). The second category comprises econometric models, which aim at identifying spillover effects exclusively from market data, without making assumptions about the dynamics of distress propagation between banks (Adrian and Brunnermeier, 2016; Brownlees and Engle, 2016). Our paper is close to the second strand of literature, as we try to understand whether market data carry information about the level of interconnectedness between banks, and how exogenous shocks can be amplified by the endogenous dynamics of financial markets.

Network models of contagion go back to the seminal work of Allen and Gale (2000), who showed how the stability of banking system is affected at equilibrium by the pattern of interconnections between banks, and to the work of Eisenberg and Noe (2001), who showed how to consistently compute a clearing vector of payments in a network of interbank claims. The relation between the structure of an interbank network and its stability has been extensively explored also within the context of non-equilibrium network models (see for instance Furfine (2003), Iori et al. (2006), Nier et al. (2007), Gai and Kapadia (2010), Cont et al. (2010), Upper (2011), Battiston et al. (2012), Fricke and Lux (2015), Bardoscia et al. (2015), Bardoscia et al. (2017), Kobayashi and Hasui (2014), Lenzu and Tedeschi (2012), Tedeschi et al. (2012)), showing in particular the existence of a tension between individual risk and systemic risk—what makes a bank individually less risky might in fact increase the risk of a systemic failure (Beale et al., 2011). More recently, these analysis have been extended beyond interbank lending networks to the study of networks of overlapping portfolios (Huang et al., 2013; Caccioli et al., 2014; Corsi et al., 2016). Although these models have been insightful to understand the dynamics of financial contagion, and in some cases they have been applied to real data (see Upper (2011) for a review of existing literature), there are clear challenges to their applicability. First, there is a lack of reliable data on banks' balance sheets, which makes it hard to calibrate models[1]. Second, to obtain a reliable assessment of systemic risk one has to capture all relevant types of interconnections between banks as the interaction between different contagion channels can significantly change the stability of the system (Caccioli et al., 2015).

Here we take the complementary approach of inferring interdependencies between banks from market data, which belongs to the second strand of literature mentioned above. The advantage of the approach with respect to network modeling is that market data are readily available, and that different types of interconnections between banks have already been aggregated by the market. The drawback is that this approach does not provide an explanation of how stress propagates between banks, and that it relies on the underlying assumption of market efficiency, which is not realistic (Shiller, 2003). Nevertheless, one can assume that, although markets are not efficient, prices do reflect to some extent the aggregate information (or expectations) about the underlying assets. There have been several contributions to this strand of the literature. In particular, Dungey et al. (2005) provide a summary of empirical models of contagion up to 2005. More recent empirical work includes Diebold and Yilmaz (2009, 2012, 2014), Caceres et al. (2010), Billio et al. (2012), Claeys and Vasicek (2014), Lucas et al. (2014), Musmeci et al. (2015) and Brownlees and Engle (2016). Of particular relevance for our paper is the work of Diebold and Yilmaz (2009, 2012, 2014) which influenced subsequent studies such as McMillan and Speight (2010), Bubák et al. (2011), Fujiwara and Takahashi (2012), Klößner and Wagner (2014), Alter and Beyer (2014), Chau and Deesomsak (2014), Demirer et al. (2015), and Fengler and Gisler (2015). This strand of contributions uses vector autoregression (VAR) and forecast error variance decomposition (FEVD) to quantify unpredictability of each of the variables in the network. By using the VAR and FEVD methods it is possible to disentangle

[1]Admati et al. (2013) report that banks tend to find ways to get around regulations in order to invest in mortgage-backed securities and derivatives via structured-investment vehicles which are off balance sheet items. Such leeway allowed by regulations creates regulatory boundaries, making it difficult for outsiders to know what banks actually report.

the contribution to unpredictability due to endogenous interdependencies from that due to exogenous shocks. Following Diebold and Yilmaz, we will refer to this endogenous component in this paper as total network connectedness, which therefore quantifies the transmission of shocks from banks within the system.

III. Data

We collect daily stock prices from January 2005 to October 2015 of banks headquartered in North America (including US and Canada), the EU, and ASEAN from Compustat database. We select only the financial institutions in the sub-industry "Banks," i.e., those large banks operating at the national level and having GICS code 40101010, and compute log returns from the daily closing prices for each bank. With the aforementioned criteria, our sample includes 10 publicly listed banks in North America (NA), 66 banks in the European Union (EU), and 39 banks in Southeast Asia (ASEAN) which survived through the period from January 2005 to October 2015.

While we could analyze rolling windows in which the number of banks that were in operation varies from one window to the next, we find that being able to see the evolution of the systems' total connectedness given a constant number of banks provides some baseline insight into how the same set of banks reacted to different economic and financial episodes over time. That being said, further research where all surviving banks were accounted for in respective rolling windows are analyzed is an interesting avenue to explore. In such case, the dimension of the rolling windows are likely to be much larger and estimation techniques such as sparsity modeling are needed.

All banks in the North American banking system have their stocks traded in the New York Stock Exchange (NYSE), while the EU and ASEAN bank stocks mostly trade in their own national stock markets. Appendix A provides lists of banks in all three regions as well as their summary statistics.

The data were analyzed over rolling windows of 300 days and over the full period. Harris (1985) recommends using a sample size where $n \geq 50 + k$ where k is the number of predictors. For our study, the minimum number of observations for each rolling window is thus $50 + 63 = 113$. We experimented with window sizes of 250, 500, and 750 days and obtained similar results in terms of the overall shape, including peaks and troughs, of total connectedness. We chose the window size of 300 days because it is a good compromise between obtaining results with reasonable margin of error which cover the period of interest (March 2006 to November 2015). The window size of 500 would provide results with a lower margin of error but cover the period from January 2007 onwards while the window size of 250 would provide results with a higher margin of error but cover the period from January 2006 onwards.

IV. Methodology

A. Total Connectedness

Following the approach introduced by Diebold and Yilmaz (2009, 2012, 2014) we use a variance decomposition where the forecast error variance of a variable is decomposed into contributions attributed to each variable in the system. The approach is based on the vector autoregression (VAR) model, introduced by Sims (1980) (see Stock and Watson (2001); Cochrane (2005); Lutkepohl (2006); Tsay (2010) for discussions, reviews and applications).

VAR estimates the value of a sets of N variables $y_{t,1}, ...y_{t,N}$ at time t from a linear combination of their values in the past by performing a multi-dimensional regression. By using the vectorial representation $\mathbf{Y}_t = (y_{t,1}, ...y_{t,N})^T$ and considering the $t-1$ lag only, the regression can be written as: $\mathbf{Y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \epsilon_t$ with $\mathbf{A}$ an $N \times N$ matrix of coefficients. By iterating this formula and expressing it in terms of an orthonormal basis of residuals $w_{i,t}$ (with $var(w_{i,t}w_{j,t}) = \delta_{i,j}$) (Cochrane, 2005), one can write:

$$y_{i,t} = \sum_{s=0}^{\infty}\sum_{j=1}^{N} \theta_{ij,s} w_{j,t-s} \quad . \tag{1}$$

The one-step ahead forecast is $\hat{\mathbf{Y}}_{t+1} = \mathbf{A}\mathbf{Y}_t$. The forecast error is the difference $y_{i,t+1} - \hat{y}_{i,t+1} = \theta_{ij,0} w_{j,t+1}$ and its variance is therefore:

$$var(y_{i,t+1} - \hat{y}_{i,t+1}) = \sum_{j,k=1}^{N} \theta_{ij,0}\theta_{ik,0} var(w_{j,t+1}, w_{k,t+1}) = \sum_{j=1}^{N} \theta_{ij,0}^2 \quad . \tag{2}$$

Each term $\theta_{ij,0}^2$ in the sum is interpreted as the contribution to the one-step forecast error variance of variable i due to shocks in variable j. Its normalized value, $c_{ij} = \theta_{ij,0}^2 / \sum_{k=1}^{N} \theta_{ik,0}^2$, is called connectedness by Diebold and Yilmaz (2009, 2012, 2014) and it is associated with the relative uncertainty spillover from variable j to variable i. In this paper we will report about the 'total connectedness', which is

$$\text{total connectedness} = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} c_{ij} \tag{3}$$

and measures the average effect that the variables have on the one-step forecast error variance. It is a measure of spillover uncertainty within the entire system.

Larger values of total connectedness correspond to unstable periods with strong influences of the variables uncertainties on each other.

We refine the original Diebold and Yilmaz (2009, 2012, 2014) methodology by introducing two technical improvements. The first improvement consists in the use of ridge regularized VAR (Tikhonov, 1963; Hoerl and Kennard, 1970), which is used to make estimations less sensitive to noise and uncertainty associated with the finite length of time series. Ridge regression introduces a penalty on the square sum of regression coefficients, thus favoring models with smaller coefficients. This improves regression performances especially for systems with a large number of variables where the covariance matrix is nearly singular (see Gruber (1998)). In practice, ridge regression consists in adding a diagonal term in the expression for the regression coefficients: $B = (XX' + \lambda I)^{-1}XY'$ with I the identity matrix and λ a coefficient that makes the inversion less sensitive to uncertainty over small eigenvalues (Tikhonov, 1963). The parameter λ must be chosen with respect to regression performances, it depends on the length of the time series and on their statistical properties. In our case, we used $\lambda = 100$ which we verified being a good compromise value for this dataset and window length 300 points [2]. We verified that results are little sensitive to variations of λ in a wide range $[100{-}1000]$. The second technical improvement consists in the use of exponential smoothing to mitigate the effects associated with sensitiveness to large variations in remote observations, Pozzi et al. (2012). Exponential smoothing computes weighted averages over the observation window with exponentially decreasing weights, $\exp(-s/\theta)$, assigned to more remote observations (here s counts the number of points from the present). In this paper we use rolling windows of size 300 days with exponential weights with characteristic length $\theta = 100$. The choice of characteristic length equal to a third of windows length was suggested as optimal by Pozzi et al. (2012).

B. Transfer entropy and Granger causality

We investigate how uncertainty in one region affects uncertainty in another region by quantifying lead-lag relationships among uncertainty spillovers. To this purpose we compute the transfer entropy associated with the daily and weekly changes in the total connectedness of the three systems.

In this paper we estimate the transfer entropy by using both linear and non-linear approaches. The transfer entropy $T_{Y\to X}$ quantifies the reduction of uncertainty on the variable X that is provided by the knowledge of the past of the variable Y taking in consideration the information from the past of X. In terms of

[2] We multiplied returns by a factor 100 in our analysis. Therefore the value $\lambda = 100$ is reasonable compared to the norm of the matrix XX', which is of order 10^4.

conditional entropies it can be written as:

$$T_{Y \to X} = H(X_t | X_{t-lag}) - H(X_t | X_{t-lag}, Y_{t-lag}) \quad (4)$$

where X_t represents the present of variable X and X_{t-lag} its lagged past. In this paper we report results for one-day lag. The conditional entropies are defined as $H(A|B) = H(A,B) - H(B)$ with $H(A,B)$ the joint entropy of variables A and B and $H(B)$ the entropy of variable B.

For what concerns the computation of these entropies, the linear approach is the standard procedure. It quantifies the additional reduction in the variance of a variable Y provided by the past of variable X and it is directly related with Granger causality (Granger (1988); Barnett et al. (2009)). In this linear case, the entropy associated with a set of variables Z is proportional to the log determinant of the covariance: $H(Z) = \frac{1}{2} \log \det(2e\pi\Sigma(Z))$, where $\Sigma(Z)$ is the covariance matrix of the variables in Z. By using Eq.4 it results that $T_{Y \to X}$ is simply given by half the logarithm of the ratio between the regression error of variable X regressed with respect to X_{t-lag} and the regression error of variable X regressed with respect to both X_{t-lag} and Y_{t-lag}. The non-linear approach estimates instead entropies by first discretizing the signal into three states, associated with a central band of values within δ standard deviations from the mean and two external bands respectively with values smaller or larger than the central band. By calling p_A^0, p_A^- and p_A^+ the relative frequencies of the observations in the three bands, entropy is estimated as $H(A) = -p_A^- \log p_A^- - p_A^0 \log p_A^0 - p_A^+ \log p_A^+$. The joint entropies are equivalently defined by the joint combination of values of the variables in the 3 bands and the transfer entropy is retrieved by applying Eq.4.

The information flow can be measured by comparing transfer entropies in the two directions. If $T_{Y \to X} > T_{X \to Y}$, then one can say that the direction of the information goes prevalently from Y to X; conversely, if $T_{X \to Y} > T_{Y \to X}$, then the direction of the information goes prevalently from X to Y. The net information flow between X and Y can be quantified as $T_{X \to Y} - T_{Y \to X}$.

We validated the statistical significance of transfer entropy by comparing our results with the null hypothesis generated by computing 10,000 values of the transfer entropy obtained by randomizing the order of the lagged variables. This provides a non-parametric null hypothesis from which p-values can be computed. We also compared this non-parametric p-value estimates with the one from F-statistics in the linear case and found comparable results.

V. Results

A. *Total connectedness*

Using data from January 2005 to October 2015, we compute the total connectedness of the three banking systems—North America, EU and ASEAN—over a rolling window of 300 days for the ten years period from March 2006 to November 2015. Figures 1, 2, and 3 report the results for each of the three systems comparing the original approach of Diebold and Yilmaz (2009) (in dashed red line) with the improved approach proposed in this paper (solid blue line). Let us first observe that the total connectedness from the two approaches have similar values and comparable behavior. We can observe that the use of ridge regularized VAR eliminates some outlying spurious peaks observed with the original method. The effect is present in all samples across the three regions and periods but is particularly evident in Fig.2 for the peak after January 2011 and January 2012. When dimensionality is high as in the case of the EU banking system, OLS estimates tend to have high variance as a result of overfitting. Ridge regression provide parameter estimates that have low variance across rolling windows, which is a manifestation of the model's ability to better generalize across different samples. This is why we observe no sudden jumps in the total connectedness when we estimate our VAR coefficients using ridge regression. More evident is the effect of exponential smoothing, which makes peaks sharper and eliminates the plateau effect due to the persistence of the influence of a peak during the whole length of the rolling window. For instance, this is especially evident in Fig.1 where in the standard VAR method the peak in total connectedness observed just after January 2009 persists creating a plateau that drops abruptly after 300 days in January 2010. Conversely the exponential weighted ridge regularized method reveal a clear peak reaching maximum around January 2009 followed by a sharp decrease. We observe that the plateau effects in standard VAR-equal-weights method sometimes hide completely peaks that are instead detected with the exponentially weighted ridge regularized method; this is for instance the case for the late 2010 North-America spillover peak visible in Fig.3 only in the exponentially weighted ridge regularized method.

Let us note that in Diebold and Yilmaz (2009), where total connectedness in equity index returns and equity index return volatilities were measured, they found that the return spillovers demonstrate "a gently increasing trend but no bursts, whereas volatility spillovers display no trend but clear bursts." Our results in Figures 1, 2, and 3 indicate that applying exponential weights onto the returns allow us to observe both trends and bursts in the return uncertainty spillovers.

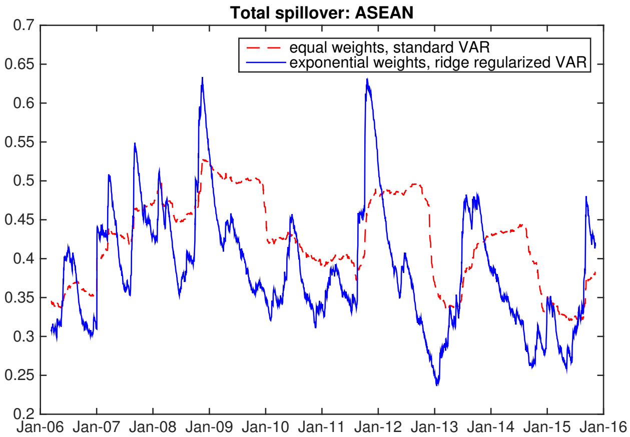

Figure 1. ASEAN banking system: Comparison between total connectedness computed with classical VAR approach (dashed red line) and the proposed approach (solid blue line) with ridge penalization and exponential smoothing. Computations are over 300-day rolling window.

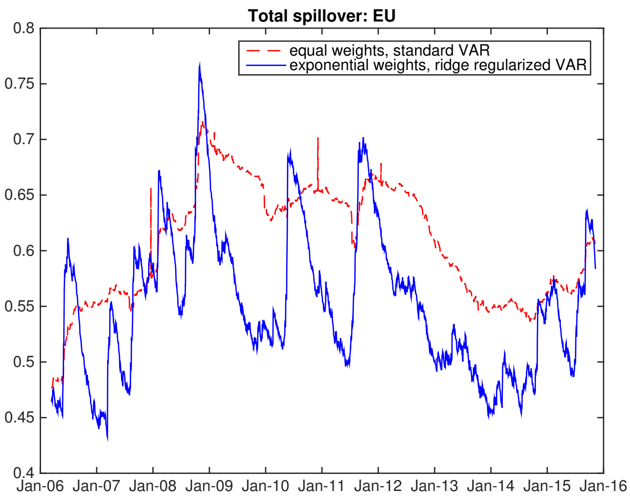

Figure 2. EU banking system: Comparison between total connectedness computed with classical VAR approach (dashed red line) and the proposed approach (solid blue line) with ridge penalization and exponential smoothing. Computations are over 300-day rolling window.

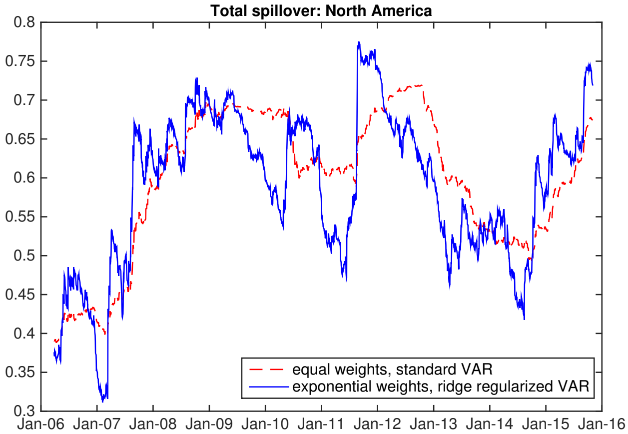

Figure 3. North American banking system: Comparison between total connectedness computed with classical VAR approach (dashed red line) and the proposed approach (solid blue line) with ridge penalization and exponential smoothing. Computations are over 300-day rolling window.

A comparison between ASEAN, EU, and North American total connectedness from the ridge regularized VAR models is presented in Figure 4, where major events are labelled on the graph when they occurred. The general shapes of the total connectedness of the three banking systems appear to be similar. Over the approximately 10-year period from March 2006 to November 2015, the values of the NA total connectedness are generally higher than those of the EU and ASEAN banking systems with the exceptions from 2006 to mid 2007, early 2011, early 2013 and mid 2014.

The fact that NA, EU and ASEAN banking systems have different levels of interconnectivity reflects the dissimilarities in the natures of the three banking systems. Our dataset include large banks operating at the national level (GICS code 40101010) that survived from the period from January 2005 to October 2015. Based on the GICS code and survival criteria, our NA system covers 2 countries (10 banks), the EU covers 17 countries (66 banks), and ASEAN covers 5 countries (39 banks). The two countries in the NA system (U.S. and Canada) have banking regulations that are more similar than those of the 17 countries in the EU and those of the 5 countries in ASEAN. In addition, the equities of the 10 banks in North America trade on the same stock exchange—the NYSE—while those of the EU and ASEAN banks trade on different national stock exchanges. Lastly, as banks tend to form business relationships with other banks that are in close proximity both geographically and from a regulatory perspective, the interbank business activities in North America are likely to be higher than those in the EU and ASEAN. These three factors contribute to stronger links and higher possibility of spillovers among the NA banks than those among the EU banks and those among the ASEAN banks. For the above reasons, total connectedness in the NA system is generally higher than those of the EU and ASEAN systems.

The number of banks in a system does not seem to be a factor influencing the level of total connectedness as there is no relationship between the number of banks and total connectedness in a system. Note that the total connectedness metric is computed on a per bank basis; it is the average of all pairwise connectedness in a system.

From visual inspection of Figure 4, we notice that variations in total connectedness of the NA banking system seems to lead those of the EU and ASEAN systems and total connectedness of the EU system seems to lead that of the ASEAN system. This prompts us to perform causality tests on the total connectedness time series of the three banking systems in order to investigate how systemic uncertainty in each region influences the others and the lead-lag relationships among them.

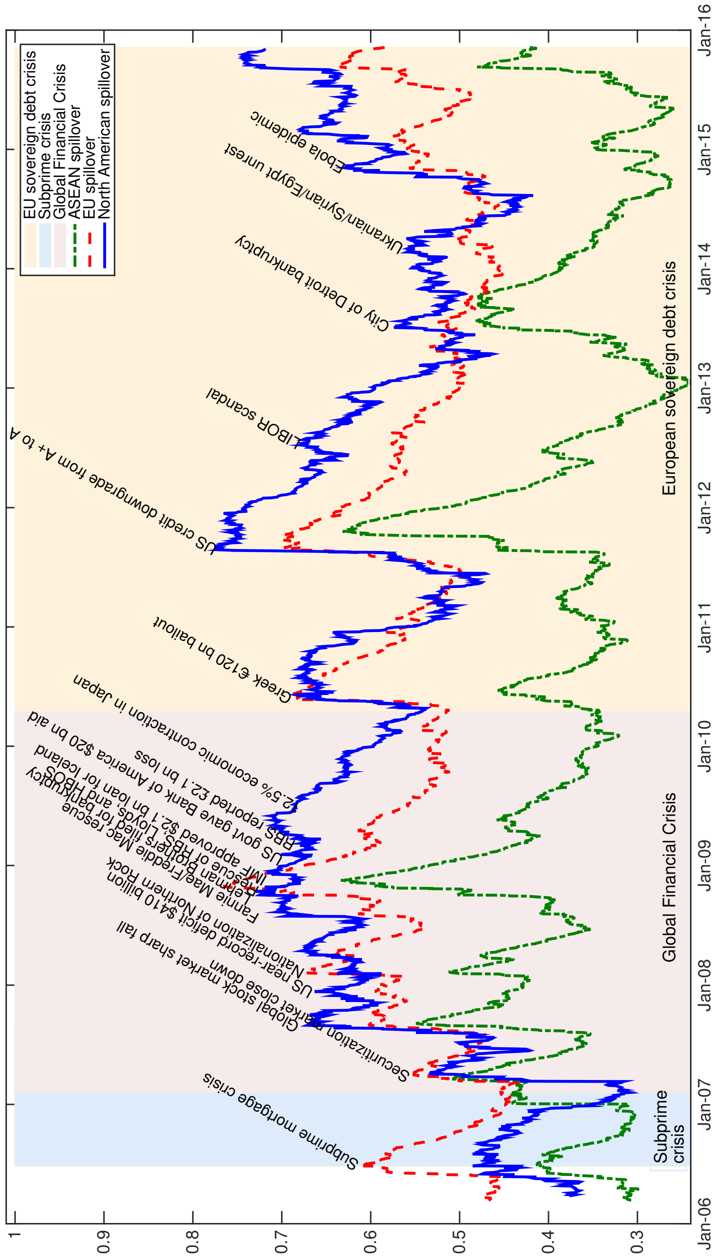

Figure 4. Total connectedness in the three banking systems (as in Figs.1, 2 and 3, solid lines). Major events associated with peaks are indicated in the figure. Computations are over 300-day rolling window.

B. Causality tests on regional total connectedness

In order to quantify the lead-lag relationships among the North American (NA), EU, and ASEAN (AS) total connectedness we compute transfer entropy and information flow between the daily changes of total connectedness in the three regions for one-day lag. Results are reported in Tab.I. Transfer entropies are estimated using both linear and non-linear approaches discussed in section IV.B. We recall that the linear measure is equivalent to Granger causality, where a significant transfer entropy corresponds to a validated Granger causality relation. The non-linear measures are computed for fluctuation bands at $\delta = 1, 2, 3$ standard deviations (see section IV.B). One can observe that there is a significant information transfer between NA and EU, NA and AS and EU and AS, that for the linear case, implies NA Granger causes EU, NA Granger causes AS and EU Granger cause AS. We observe that the non-linear estimation gives consistent results with the linear estimate for all values of δ, demonstrating robustness of the result. We also observe that there are significant causal relations also in the opposite directions. Given the extended time-lags between the three regions it is fair to question whether one-day time lag and one-day time horizon will affect asymmetrically markets depending on their relative opening hours. We therefore test the flow of information across regions for time-horizon and lag of 5 days instead of one day. The results for the transfer entropies and information flow, performed for the entire period on non-overlapping 5-day returns, are reported in Tab. II. We observe that results are consistent with the ones for one-day time horizon and lag reported in Tab. I with the main difference being the lower statistical significance. This is expected because the time series for the 5-day changes are five times shorter than the ones for daily changes.

Table I. Quantification of transfer entropy between regional total connectedness: March 28, 2006-November 2, 2015 (full sample). From daily changes in the total connectivity using one day lag.

method	$TE_{NA\rightarrow EU}$	$TE_{EU\rightarrow NA}$	Net Information Flow
linear	0.004722^{**}	0.001354^{*}	0.003369
non-linear treshold σ	0.005251^{***}	0.006711^{**}	-0.001460
non-linear treshold 2σ	0.003980^{***}	0.002012^{*}	0.001968
non-linear treshold 3σ	0.004939^{***}	0.000561	0.004378
method	$TE_{NA\rightarrow AS}$	$TE_{AS\rightarrow NA}$	Net Information Flow
linear	0.017336^{***}	0.008931^{***}	0.008405
non-linear treshold σ	0.008789^{***}	0.005837^{**}	0.002953
non-linear treshold 2σ	0.005348^{***}	0.002305^{*}	0.003042
non-linear treshold 3σ	0.003150^{**}	0.002803^{***}	0.000348
method	$TE_{EU\rightarrow AS}$	$TE_{AS\rightarrow EU}$	Net Information Flow
linear	0.005659^{**}	0.003633^{**}	0.002026
non-linear treshold σ	0.005553^{**}	0.001262	0.004291
non-linear treshold 2σ	00.005960^{***}	0.000228	0.005732
non-linear treshold 3σ	0.004238^{***}	0.002118^{***}	0.002120

* p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

Table II. Quantification of transfer entropy between regional total connectedness: March 28, 2006-November 2, 2015 (full sample). From weekly changes (5 days) in the total connectivity using five days lag.

method	$TE_{NA\to EU}$	$TE_{EU\to NA}$	Net Information Flow
linear	0.008003^{*}	0.001255	0.006747
non-linear treshold σ	0.009204	0.009474	-0.000271
non-linear treshold 2σ	0.017228^{***}	0.003196	0.014032
non-linear treshold 3σ	0.024087^{***}	0.002335^{*}	0.021752

method	$TE_{NA\to AS}$	$TE_{AS\to NA}$	Net Information Flow
linear	0.017200^{**}	0.003703	0.013497
non-linear treshold σ	0.010598^{*}	0.004354	0.006244
non-linear treshold 2σ	0.006509	0.006475	0.000034
non-linear treshold 3σ	0.002107	0.006805^{***}	-0.004698

method	$TE_{EU\to AS}$	$TE_{AS\to EU}$	Net Information Flow
linear	0.022020^{**}	0.000619	0.021401
non-linear treshold σ	0.021641^{***}	0.002374	0.019267
non-linear treshold 2σ	0.022964^{***}	0.002900	0.020063
non-linear treshold 3σ	0.007488^{**}	0.000405	0.007083

* p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

VI. Conclusion

We investigate regional and inter-regional uncertainty spillovers in the North American, EU, and ASEAN banking systems during a period characterized by great regional and global financial stress (2005-2015). Uncertainty and financial instability is quantified by means of total network connectedness, that we measure improving the method of Diebold and Yilmaz. We demonstrate that exponential smoothing and ridge regression provide better defined peaks in the temporal analysis and avoid the occurrence some spurious peaks. We observe that the North-American system appears to be consistently more interconnected than the EU, which in turn is more interconnected than the ASEAN network. Similarly to previous analysis of Diebold an Yilmaz on other systems, our empirical analysis of the North-American, ASEAN and EU banking networks shows that increased connectivity corresponds to periods of higher distress in the system. We observe that all large peaks of total network connectedness are associate with identifiable major exogenous events. Despite some of these events being related to specific regions, the effects are seen similarly across the three banking systems, which reveal similar patterns of peaks and troughs in the variations of their total network connectedness. However, such variations are not perfectly synchronous across the regions, and causality patterns are discovered by using transfer entropy. The analysis reveals that the North American banking system is the most influential, causing the largest effects on the other systems. However, feedback effects are measured with significant causal relations also in the opposite directions. The results are demonstrated to be robust with respect to changes in the method used to compute the transfer entropy, changes in the values of parameters, and with respect to the use of daily or weekly returns in the analysis.

To summarize, the contribution of this paper is three folds. First, we improve technical aspect of the VAR estimation, allowing for better identification of events concentrated at specific times, which leads to more accurate and insightful interpretation of the results. Second, we focus on connectedness in banking sector, while previous studies based on the Diebold and Yilmaz methodology analyzed networks of financial institutions. In particular, we analyze the North American, EU and ASEAN banking systems individually and show that, despite the regions' geographical distances, they are affected in various degrees by major financial crisis events originated in dominant regions such as the North American and EU banking systems. Third, we originally perform a causality analysis on the regional connectedness time series generated through the Diebold and Yilmaz's method. Our analysis suggests that a regional disaggregated investigation has the advantage of introducing a predictive component to this methodology. While the network total connectedness measure identifies increase in regional uncertainty associated with major events that shake the markets, the causality relation between total connectedness in different regions, introduced in this paper, provides a quantitative characterization of the flow of uncertainty form region to region, that could be interpreted as the result of contagion. To the best of our knowledge, this causality analysis is the first of its kind.

As future directions we will compare this approach with other information theoretic measures with the aim to find a framework that is capable to qualify financial uncertainty and its causal effects at all levels of aggregation, from a local single-variable perspective to the global world-market view.

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Declaration of interests

The authors report no conflicts of interest.

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Appendix A. List and summary statistics of banks in the sample

Table III. List of banks that are headquartered in North America (Canada and the U.S.) and have actively traded between 2005-2015

	Bank name	Country	Daily mean return (%)	Daily volatility (%)
1.	Canadian Imperial Bank (CIBC)	CAN	0.01	1.82
2.	Bank of Montreal (BMO)	CAN	0.01	1.69
3.	Royal Bank of Canada (RBC)	CAN	0.03	1.73
4.	Toronto Dominion Bank (TD)	CAN	0.03	1.65
5.	Bank of Nova Scotia (BNS)	CAN	0.01	1.72
6.	Citigroup (CITI)	USA	-0.08	3.70
7.	Bank of America Corp (BAC)	USA	-0.04	3.51
8.	Wells Fargo & Co (WFC)	USA	0.02	2.86
9.	JP Morgan Chase & Co (JPM)	USA	0.02	2.64
10.	US Bancorp (USB)	USA	0.01	2.32

Table IV. List of banks that are headquartered in Southeast Asia and have actively traded between 2005-2015.

	Bank	Country	Market cap ($ billion)	Average return (%)	Volatility (%)
1	Bank Rakyat Indonesia	IDN	20.43	0.07	2.56
2	Bank Permata	IDN	0.54	0.02	1.93
3	Bank Danamon	IDN	2.23	0.00	2.73
4	Bank Maybank Indonesia	IDN	0.79	0.00	2.67
5	Bank Cimb Niaga	IDN	1.07	0.02	2.51
6	Panin Bank	IDN	0.17	0.03	2.68
7	Bank Negara Indonesia	IDN	6.66	0.04	2.50
8	Bank Central Asia	IDN	23.21	0.08	2.06
9	Bank Mandiri	IDN	15.75	0.05	2.54
10	Public Bank	MYS	16.15	0.04	0.90
11	Malayan Banking	MYS	18.70	0.00	1.23
12	RHB Capital	MYS	3.73	0.03	1.58
13	AMMB Holdings	MYS	3.04	0.01	1.51
14	AFFIN Holdings	MYS	0.97	0.01	1.65
15	Alliance Financial Group	MYS	1.15	0.01	1.52
16	BIMB Holdings	MYS	1.35	0.03	2.13
17	CIMB Group Holdings	MYS	7.92	0.02	1.54
18	Hong Leong Bank	MYS	6.17	0.03	1.14
19	Philippine National Bank	PHL	1.20	0.03	2.39
20	Bank of Philippine Islands	PHL	6.97	0.03	1.79
21	China Banking Corp	PHL	1.36	0.04	1.39
22	Metropolitan Bank and Trust	PHL	4.67	0.05	2.12
23	Security Bank Corp	PHL	1.86	0.07	1.87
24	Rizal Commercial Bank Corp	PHL	0.94	0.03	2.19
25	Union Bank	PHL	1.22	0.05	1.77
26	BDO Unibank	PHL	7.33	0.05	2.04
27	United Overseas Bank	SGP	19.62	0.01	1.49
28	DBS Group Holdings	SGP	25.23	0.01	1.49
29	Oversea-Chinese Banking	SGP	22.71	0.02	1.33
30	Krung Thai Bank	THA	6.79	0.02	2.11
31	Siam Commercial Bank	THA	11.44	0.03	2.02
32	Bangkok Bank	THA	8.04	0.02	1.81
33	Bank of Ayudhya	THA	6.15	0.03	2.41
34	Kasikornbank	THA	10.94	0.04	1.97
35	TMB Bank	THA	3.12	-0.01	2.40
36	Kiatnakin Bank	THA	0.91	0.00	1.94
37	Tisco Financial Group	THA	0.96	0.02	2.11
38	Thanachart Capital	THA	14.3	0.03	2.13
39	CIMB Thai Bank	THA	0.76	-0.01	2.75

Table V. List of banks that are headquartered in the EU and have actively traded between 2005-2015 (1).

	Bank	Country	Daily return (%)	Volatility (%)
1	Oberbank Ag	AUT	0.02	0.38
2	Erste Group Bk Ag	AUT	-0.01	2.95
3	KBC Group Nv	BEL	0.00	3.50
4	Dexia Sa	BEL	-0.21	7.76
5	Hellenic Bank	CYP	-0.08	3.08
6	Komercni Banka As	CZE	0.01	2.10
7	IKB Deutsche Industriebank	DEU	-0.13	3.90
8	Commerzbank	DEU	-0.08	3.09
9	DVB Bank Ag	DEU	0.03	1.38
10	HSBC Trinkaus & Burkhardt	DEU	0.00	1.73
11	Comdirect Bank Ag	DEU	0.02	1.83
12	Deutsche Postbank Ag	DEU	0.00	2.15
13	Danske Bank As	DNK	0.01	2.11
14	Jyske Bank	DNK	0.02	1.94
15	Nordea Invest Fjernosten	DNK	0.01	1.43
16	Sydbank As	DNK	0.03	1.93
17	Banco Santander Sa	ESP	0.00	2.16
18	BBVA	ESP	-0.01	2.12
19	Banco Popular Espanol	ESP	-0.07	2.30
20	Bankinter	ESP	0.01	2.28
21	Banco De Sabadell Sa	ESP	-0.02	1.89
22	BNP Paribas	FRA	0.00	2.56
23	Natixis	FRA	-0.01	3.12
24	Societe Generale Group	FRA	-0.02	2.86
25	Credit Agricole Sa	FRA	-0.02	2.78
26	CIC (Credit Industriel Comm)	FRA	0.00	1.41
27	Barclays Plc	GBR	-0.03	3.23
28	HSBC Hldgs Plc	GBR	-0.02	1.72
29	Royal Bank of Scotland Group	GBR	-0.10	3.91
30	Standard Chartered Plc	GBR	0.00	2.44
31	Lloyds Banking Group Plc	GBR	-0.05	3.37
32	Piraeus Bank Sa	GRC	-0.22	5.04
33	Attica Bank Sa	GRC	-0.23	5.88

Table VI. (cont.) List of banks that are headquartered in the EU and have actively traded between 2005-2015 (2).

	Bank	Country	Daily return (%)	Volatility (%)
34	Eurobank Ergasias Sa	GRC	-0.31	5.52
35	National Bank of Greece	GRC	-0.20	4.81
36	Alpha Bank Sa	GRC	-0.15	4.69
37	Zagrebacka Banka	HRV	0.00	2.58
38	Privredna Banka Zagreb Dd	HRV	0.01	2.37
39	OTP Bank Plc	HUN	0.00	2.63
40	Unicredit Spa	ITA	-0.05	2.90
41	Credito Emiliano Spa	ITA	0.00	2.26
42	Intesa Sanpaolo Spa	ITA	0.00	2.61
43	Banca Popolare Di Sondrio	ITA	-0.01	1.83
44	Banca Carige Spa Gen & Imper	ITA	-0.10	2.39
45	Banco Desio Della Brianza	ITA	-0.02	1.76
46	Banco Popolare	ITA	-0.06	2.86
47	Banca Popolare Di Milano	ITA	-0.03	2.78
48	Banca Monte Dei Paschi Siena	ITA	-0.12	2.96
49	Bank of Siauliai Ab	LTU	-0.06	2.97
50	ING Groep Nv	NLD	-0.01	3.14
51	Van Lanschot Nv	NLD	-0.03	1.62
52	Mbank Sa	POL	0.05	2.34
53	Bank Handlowy W Warzawie Sa	POL	0.01	2.05
54	ING Bank Slaski Sa	POL	0.04	1.90
55	Bank BPH S.A.	POL	-0.09	4.48
56	Bank Millennium Sa	POL	0.03	2.62
57	Bank Plsk Kasa Opk Grp Pekao	POL	0.00	2.26
58	Bank Zachodni Wbk Sa	POL	0.04	2.15
59	Getin Holding Sa	POL	-0.02	3.16
60	Powszechna Kasa Oszczednosci	POL	0.00	2.02
61	Banco BPI Sa	PRT	-0.03	2.46
62	Banco Comercial Portugues Sa	PRT	-0.09	2.76
63	Svenska Handelsbanken	SWE	0.02	1.86
64	Skandinaviska Enskilda Bank	SWE	0.01	2.55
65	Nordea Bank Ab	SWE	0.02	2.05
66	Swedbank Ab	SWE	0.01	2.53