Volatility transmission between stock and foreign exchange markets: A connectedness analysis

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Abstract

This paper empirically investigates volatility transmission among stock and foreign exchange markets in seven major world economies during the period July 1988 to May 2018. To this end, we first perform a static and dynamic analysis to measure the total volatility connectedness in the entire period (the system-wide approach) using a framework recently proposed by Diebold and Yılmaz (2014). Second, we make use of a dynamic analysis to evaluate the net directional connectedness for each market. To gain further insights, we examine the time-varying behavior of net pair-wise directional connectedness during the financial turmoil periods experienced in the sample period. Our results suggest that slightly more than half of the total variance of the forecast errors is explained by shocks across markets rather than by idiosyncratic shocks. Furthermore, we find that volatility connectedness varies over time, with a surge during periods of increasing economic and financial instability.

JEL Classification Codes: C53; F31; G15

Keywords: Stock markets; Foreign exchange rates; Market Linkages; Vector Autoregression; Variance Decomposition

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1. Introduction

Economic and financial globalization generates intense co-movement and spillovers both across and within asset classes. As Chinn (1989) argued, the greater integration of equity markets, that has led to a greater link between these markets and to substantial international financial flows, means that equity markets have an increasing influence on exchange rate. This influence can help to explain some excess variability in foreign exchange markets, since equity markets have a tendency to develop significant pricing errors [see, e. g., Shiller (1981) and Campbell and Shiller (1987)]. In fact, Sarantis (1987) expanded Branson (1976, 1977)'s portfolio-balance model of exchange rate determination by introducing equity assets into the portfolio of investors, obtaining better results than the original specification.

The interdependence of stock price returns and exchange rate changes has been extensively examined in the empirical literature with mixed findings on the directional causality (see Adler and Dumas, 1984; Booth and Rotenberg, 1990; Jorion, 1990; Sercu and Vanhulle, 1992; Smith 1992; Bodnar and Gentry, 1993; Amihud, 1994; Inci and Lee, 2014; and Liang *et al.*, 2013; among others)¹. Likewise, empirical evidence on the dynamic linkage between stock and currency market volatilities also provides conflicting findings. Early studies, such as Jorion (1990), suggested that exchange rate fluctuations do not affect stock return volatility, while others (see, for example, Dumas and Solnik, 1995; Roll, 1992) identified the existence of a strong linkage. More recently, Kanas (2000) has analyzed volatility transmission between stock and currency markets in the USA, the UK, Japan, Germany, France and Canada finding evidence of spillovers between stock returns and exchange rate changes for five of the six countries analyzed (with Germany being the exception). Yang and Doong (2004) investigated volatility spillovers between stock prices and exchange rates for the G-7 countries finding that stock markets play a relatively more important role than foreign exchange markets in the second moment interactions and spillovers. Wang *et al.* (2013) use a dependence-switching copula model to describe the dependence structure between the stock and foreign exchange markets for six major industrial countries (Canada, France, Germany, Italy, Japan and the United Kingdom) over the 1990–2010 period concluding

¹ Hau and Rey (2006) show strong theoretical and empirical links between equity and exchange rate markets, while Doukas *et al.* (2003) explain why firms are affected by exchange rate exposure.

that the dependence and tail dependence among the above four market statuses are asymmetric for most countries in the negative correlation regime, but symmetric in the positive correlation. Mun (2012), investigating the joint response of stock and foreign exchange market returns to macroeconomic surprises using US and Japanese data, finds that US stock markets are asymmetrically responsive to domestic developments in output growth and interest rates but are not influenced by macroeconomic surprises from Japan. Using copulas, Reboredo *et al.* (2016) find a positive relationship between stock prices and currency values in emerging economies with respect to the US dollar and the euro. Finally, Kilic (2017) examines the contagion effects of U.S. Dollar and Chinese Yuan by the application of a bivariate Hawkes stochastic jump process.

In this study we will focus on the volatility interconnection between the stock and currency markets of seven major world economies making use of Diebold and Yilmaz's (2014) measures of connectedness². Diebold and Yilmaz's (2014) connectedness framework is closely linked with both modern network theory (see Glover and Richards-Shubik, 2014) and modern measures of systemic risk (see Ang and Longstaff, 2013 or Acemoglu *et al.*, 2015) and has been used by Diebold and Yilmaz (2015) for defining, measuring, and monitoring connectedness in financial and related macroeconomic environments (cross-firm, cross-asset, cross-market, cross-country, etc.). The degree of connectedness, on the other hand, measures the contribution of individual units to systemic network events, in a fashion very similar to the conditional value at risk (CoVaR) of this unit (see, e. g., Adrian and Brunnermeier, 2008).

Our study extends and complements the existing literature by providing a novel perspective on the interdependence of stock markets and foreign exchange markets. Although a substantial amount of literature has used different extensions of Diebold and Yilmaz's (2012) previous methodology to examine spillovers and transmission effects in different financial markets³, to the best of our knowledge it has not been applied to

² The connectedness methodology has several advantages over the alternative approach of focusing on contemporaneous correlations (corrected or not for volatility). First, while correlation is a symmetrical measure, connectedness is an asymmetrical one, so the procedure provides information on the direction and magnitude of the volatility transmission (from country *A* to country *B*, from country *B* to country *A*, or both). Second, by investigating dynamic connectedness through a rolling window, we can evaluate how the strength of the connectedness evolves over time, allowing us to detect episodes of sudden and temporary increases in volatility transmission.

³ Awartania *et al.* (2013), Lee and Chang (2013), Chau and Deesomsak (2014) and Cronin (2014) apply this methodology to examine spillovers in the United States' markets; Yilmaz (2010), Zhou *et al.* (2012) or Narayan *et al.*

explore volatility transmission between the stock and currency markets of seven major world economies. Since volatility reflects the extent to which the market evaluates and assimilates the arrival of new information, the analysis of its transmission pattern might provide useful insights into the characteristics and dynamics of foreign exchange and stock markets. So, since the information gathered would provide a barometer for the vulnerability of these markets, we consider that to empirically examine volatility spillovers is a novel and relevant issue. Moreover, during crises, markets' volatilities tend to increase rapidly, and financial analysts seem to believe that volatility shocks in one market can easily have an impact on the other markets, being the connectedness analysis ideal for testing net directional spillovers, identifying when and where they started in a given market and how subsequently spread to the rest of markets.

The rest of the paper is organized as follows. Section 2 presents Diebold and Yılmaz (2014)'s methodology for assessing connectedness in financial market volatility, and the empirical results (both static and dynamic) obtained for our sample of seven major world economies (a system-wide measure of connectedness). In Section 3 we examine the time-varying behavior of net pair-wise directional connectedness during the financial turmoil periods experienced during in the sample period. Finally, Section 4 summarizes the findings and offers some concluding remarks.

2. Connectedness analysis

2.1. Econometric methodology

The main tool for measuring the amount of connectedness is based on a decomposition of the forecast error variance, which we will now briefly describe.

Given a multivariate empirical time series, the forecast error variance decomposition results from the following steps:

(2014) focus on Asian countries; Apostolakisa and Papadopoulos (2014) and Tsai (2014) examine G-7 economies, Duncan and Kabundi (2013) centre their analysis on South African markets, Antonakakisa and Floros (2016): study dynamic interdependencies among the housing market and stock market in the United Kingdom, Grosche and Hecke (2016) investigate volatility spillovers between agricultural, crude oil, real estate, and other financial markets, Fernández-Rodríguez *et al.* (2016) use connectedness analysis to assess financial stress transmission in EMU sovereign bond market volatility and Greenwood-Nimmo *et al.* (2016) study spillovers among daily returns and innovations in the option-implied risk-neutral volatility and skewness of the G10 currencies.

1. Fit a standard vector autoregressive (VAR) model to the series.
2. Using series data up to and including time t , establish an H period-ahead forecast (up to time $t + H$).
3. Decompose the error variance of the forecast for each component with respect to shocks from the same or other components at time t .

Diebold and Yilmaz (2014) propose several connectedness measures built from pieces of variance decompositions in which the forecast error variance of variable i is decomposed into parts attributed to the various variables in the system. This section provides a summary of their connectedness index methodology.

Let us denote by d_{ij}^H the ij -th H -step variance decomposition component (i.e., the fraction of variable i 's H -step forecast error variance due to shocks in variable j). The connectedness measures are based on the “non-own”, or “cross”, variance decompositions, $d_{ij}^H, i, j = 1, \dots, N, i \neq j$.

Consider an N -dimensional covariance-stationary data-generating process (DGP) with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \dots$, $E(u_t, u_t') = I$. Note that Θ_0 need not be diagonal. All aspects of connectedness are contained in this very general representation. Contemporaneous aspects of connectedness are summarized in Θ_0 and dynamic aspects in $\{\Theta_1, \Theta_2, \dots\}$. Transformation of $\{\Theta_1, \Theta_2, \dots\}$ via variance decompositions is needed to reveal and compactly summarize connectedness. Diebold and Yilmaz (2014) propose a connectedness table such as Table 1 to understand the various connectedness measures and their relationships. Its main upper-left $N \times N$ block, which contains the variance decompositions, is called the “variance decomposition matrix,” and is denoted by $D^H = [d_{ij}^H]$. The connectedness table increases D^H with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

[Insert Table 1 here]

The off-diagonal entries of D^H are the parts of the N forecast-error variance decompositions of relevance from a connectedness perspective. In particular, the *gross pair-wise directional connectedness* from j to i is defined as follows:

$$C_{i \leftarrow j}^H = d_{ij}^H. \quad (1)$$

Since in general $C_{i \leftarrow j}^H \neq C_{j \leftarrow i}^H$, the *net pair-wise directional connectedness* from j to i , can be defined as:

$$C_{ij}^H = C_{j \leftarrow i}^H - C_{i \leftarrow j}^H. \quad (2)$$

As for the off-diagonal row sums in Table 1, they give the share of the H -step forecast-error variance of variable x_i coming from shocks arising in other variables (all others, as opposed to a single other), while the off-diagonal column sums provide the share of the H -step forecast-error variance of variable x_i going to shocks arising in other variables. Hence, the off-diagonal row and column sums, labelled “from” and “to” in the connectedness table, offer the total directional connectedness measures. In particular, total directional connectedness from others to i is defined as

$$C_{i \leftarrow \bullet}^H = \sum_{\substack{j=1 \\ j \neq i}}^N d_{ij}^H, \quad (3)$$

and *total directional connectedness* to others from i is defined as

$$C_{\bullet \leftarrow i}^H = \sum_{\substack{j=1 \\ j \neq i}}^N d_{ji}^H. \quad (4)$$

We can also define *net total directional connectedness* as

$$C_i^H = C_{\bullet \leftarrow i}^H - C_{i \leftarrow \bullet}^H. \quad (5)$$

Finally, the grand total of the off-diagonal entries in D^H (equivalently, the sum of the “from” column or “to” row) measures *total connectedness*:

$$C^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ j \neq i}}^N d_{ij}^H. \quad (6)$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated as before, because the variance of a weighted sum is not an appropriate sum of variances; in this case, methodologies for providing orthogonal innovations like traditional Cholesky-factor identification may be sensitive to ordering. So, following Diebold and Yilmaz (2014), a generalized VAR decomposition (GVD), invariant to ordering, proposed by Koop *et al.* (1996) and Pesaran and Shin (1998) will be used. The H -step generalized variance decomposition matrix is defined as $D^{gH} = [d_{ij}^{gH}]$, where

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i \Theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i \Theta_h \Sigma \Theta'_h e_j)} \quad (7)$$

In this case, e_j is a vector with j th element unity and zeros elsewhere, Θ_h is the coefficient matrix in the infinite moving-average representation from VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, σ_{jj} being its j th diagonal element. In this GVD framework, the lack of orthogonality means that the rows of d_{ij}^{gH} do not have sum unity and, in order to obtain a generalized connectedness

index $\tilde{D}^g = [\tilde{d}_{ij}^g]$, the following normalization is necessary: $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$, where by

construction $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$.

The matrix $\tilde{D}^g = [\tilde{d}_{ij}^g]$ permits us to define similar concepts as defined before for the orthogonal case, that is, *total directional connectedness*, *net total directional connectedness*, and *total connectedness*.

2.2. Data

The data consist of daily closing stock prices denominated in local currency for the US (Standard & Poor's 500 composite index, S&P500), the Euro Area (Eurostoxx 50 Index), Japan (Nikkei 225 index), the UK (Financial Times Stock Exchange 100 Index, FTSE100), Australia (All Ordinaries Index, AOI), Switzerland (Swiss Market Index, SMI) and Canada (Toronto Stock Exchange Composite Index, TSX). The exchange rate series for each country is a trade-weighted exchange rate, to account for each country's diverse investment positions in foreign equities. In particular, we examine the following effective exchange rates: US Dollar (USD), Euro (EUR), Australian dollar (AUD), Swiss franc (CHF), Canadian dollar (CAD), British pound (GBP) and Japanese yen (JPY)⁴. The stock price data has been extracted from Thomson Reuters Datastream. The exchange rate series are the Bank of England trade-weighted exchange rates. Note that focusing on these seven major world economies, we cover 174.9% of global foreign exchange market turnover⁵.

Weekly data is used to partially overcome the potential problem of nonsynchronous data, which may arise because there are instants in which markets are closed in one country and open in another (Burns and Engle (1998) and Lo and MacKinlay (1990) study the effects of this problem). The returns are computed as log differences using Wednesday to Wednesday closing index prices to avoid any potential day of the week biases (see Brailsford (1995) and Griffin et al. (2007) among others). If a particular Wednesday happens to be a non-trading day, then closing values are recorded on the previous trading day. Our final sample covers the period 6 July 1988 to 8 May 2018 (i.e., a total of 1,558 observations), spanning several important financial market episodes in addition to the global financial crisis of 2007-2008 – in particular, the tequila crisis in 1994, the Asian crisis in 1997-1998, the ruble crisis in 1998, the dotcom crash in 2001, the euro area sovereign debt crisis from 2009 onwards and the UK decision to leave the European Union after the referendum held on June 2016.

⁴ We use a trade-weighted exchange rate to account for each country's diverse investment positions in foreign equities (see Tesar and Werner, 1995; and Kanas, 2000).

⁵ Average of currency distribution of global foreign exchange market turnover over 2001, 2004, 2007, 2010, 2013 and 2016 Bank for International Settlements (2016). Because two currencies are involved in each transaction, the sum of the percentage shares of individual currencies totals 200% instead of 100%.

2.3. Static (full-sample, unconditional) analysis

The full-sample connectedness table appears as Table 2. As mentioned above, the ij th entry of the upper-left 14x14 market submatrix gives the estimated ij th pair-wise directional connectedness contribution to the forecast error variance of market i 's volatility yields coming from innovations to market j . Hence, the off-diagonal column sums (labelled TO) and row sums (labelled FROM) gives the total directional connectedness to all others from i and from all others to i respectively. The bottom-most row (labelled NET) gives the difference in total directional connectedness (to-from). Finally, the bottom-right element (in boldface) is the total connectedness.

[Insert Table 2 here]

As can be seen, the diagonal elements (own connectedness) are the largest individual elements in the table (ranging from 27.51% for Eurostoxx 50 to 66.15% for CHF), being higher in foreign exchange markets (with an average of 52.18%) than in stock markets (with an average of 35.89%). Nevertheless, total directional connectedness (from others or to others) tends to be much larger for stock markets, except the contribution to others by AOI and the Nikkei 225 Index. In addition, the spread of the “from” degree distribution is noticeably greater than that of the “to” degree distribution for seven out of the fourteen cases under study.

Regarding pair-wise directional connectedness (the off-diagonal elements of the upper-left 14x14 submatrix), the highest observed pair-wise connectedness is from FTSE100 to Eurostoxx 50 (19.49%). The pair-wise connectedness from TSX to SP100 (17.15%) is the second-highest. The highest value of pair-wise directional connectedness between foreign exchange markets is from CHF to EUR (14.50%), followed by that from CAD to AUD (13.94%). The highest value of pair-wise directional connectedness between stock markets and foreign markets is from TSX to AUD (8.48%), followed by that from TSX to CAD (6.77%). The total directional connectedness from others, which measures the share of volatility shocks received from other market in the total variance of the forecast error for each market, ranges between 33.84% (CHF) and 73.21% (FTSE100). As for the total directional connectedness to others, our results suggest that it varies from a low of 25.85% for GBP to 75.82% for FTSE100. Finally, we obtain a value of

56.01% for the total connectedness between the fourteen markets under study for the full sample (system-wide measure), indicating that 43.99% of the variation is due to idiosyncratic shocks. This result sharply contrasts with the value of 78.3% obtained by Diebold and Yilmaz (2014) for US financial institutions and with the value of 97.2% found by Diebold and Yilmaz (2012) for international financial markets.

2.4 Dynamic (rolling, conditional) analysis

The full-sample connectedness analysis provides a good characterization of “unconditional” aspects of the connectedness measures. However, it does not help us to understand the connectedness dynamics. The appeal of connectedness methodology lies in its use as a measure of how quickly return or volatility shocks spread across countries as well as within a country. This section presents an analysis of dynamic connectedness which relies on rolling estimation windows.

The dynamic connectedness analysis starts with total connectedness (2.4.1), and then moves on to net directional connectedness across countries (2.4.2).

2.4.1. Total connectedness

The rolling-window approach has the advantages of tremendous simplicity and coherence with a wide variety of possible underlying time-varying parameter mechanisms. Rolling windows do, however, require choice of window width, in a manner precisely analogous to bandwidth choice in density estimation. In this paper we focus on a 200-day rolling-sample windows and using 10 days as the predictive horizon for the underlying variance decomposition. As expected, the connectedness index plotted in Figure 1 shows a time-varying pattern over the sample period.

The total volatility connectedness index during the period between 1992 and 1994 was relatively high, 41% on average. After the tequila crisis in 1994, began an upward trend that was successively reinforced by the Asian crisis (July 1997) and the ruble crisis (August 1998). After reached a peak in October 1998 there was an obvious downward trend that was strengthened after the dotcom crash (March 2000) and a period of relatively stability around the value of 45%. Interestingly, the events of September 11,

2001, and the wars of Afghanistan and Iraq did not seem to have a significant impact on total volatility connectedness. Following the subprime crisis and the complete evaporation of liquidity that initiated the global financial crisis (August 2007), there was an increase in volatility connectedness that reaches its peak in April 2009⁶, coinciding with a statement by the European Central Bank (ECB) expressing its fears of a slowdown in financial market integration that triggered a first episode of the European sovereign crisis. It was only after a forceful response of central by implementing nonstandard monetary policies and the ECB's President Mario Draghi's statement that he would do "whatever it takes to preserve the euro" (July 2012) that there was a substantial decrease in the level of total connectedness. Moreover, after the collapse of the Russian ruble in June 2014 there was an intensification of connectedness. Finally, we detect a new increase in the degree of market volatility connectedness after the Brexit referendum (June 2016), being further strengthened after the United Kingdom formally begun negotiations to leave the EU (March 2017). Our findings are consistent with earlier literature in that the linkage between markets intensifies during periods of increasing economic and financial instability (see, e. g., Kolb, 2011; and Leung *et al.*, 2017), implying a loss of diversification just when it is needed most.

[Insert Figure 1 here]

The dynamic analysis of the total connectedness of returns gave a clear understanding of the dynamics of connectedness over the full sample period, and provides insight into the system as a whole. The next step is to look at the dynamics of directional connectedness over the same period. To better evaluate the differences between the 'to others' and 'from others' directional connectedness, the evolution of the entire 'net' degree distribution is examine in the next section.

2.4.2. Net directional connectedness

The net directional connectedness index provides information about how much each market's volatility contributes in net terms to other market's volatilities and, like the full

⁶ This finding is in line with to those of Diebold and Yilmaz (2014) where the total connectedness of select companies in the financial services industry increased during the global financial crisis.

sample dynamic measure presented in the previous section, also relies on rolling estimation windows. The time varying-indicators are displayed in Figures 2, 3 and 4 for stock markets, foreign exchange markets and national stock markets to foreign exchange market respectively.

[Insert Figures 2 to 4 here]

Regarding the stock markets, it is noticeable that in the cases of the Eurostoxx 50 (82.27%), SMI (64.62%), TSX (81.02%), FTSE100 (95.94%), more than 50% of the computed values are positive, indicating that during most of the sample period, the stock market volatility in these markets influenced that of the rest of markets, whereas for the remaining stock markets the opposite is true (i.e., they are net receivers during most of the period). Interestingly, the SP500 becomes volatility trigger after the outbreak of the global financial crisis while Eurostoxx 50 becomes volatility receiver. When we split the sample into crises periods, some stimulating patterns emerge. The Tequila crisis intensified the volatility spillovers from the US, European and British stock markets. The 1997 Asian crisis seems to have specially affected the US, British and Japanese stock markets, while the ruble crisis played a significant role in the transmission of volatility from the European, Canadian and British stock markets. Additionally, the successive European sovereign crises especially impacted in volatility transfer from the US, Swiss, Canadian and British stock markets. Finally, the Brexit referendum caused instability transmission in all markets under study, except the FTSE100 that registered intense volatility influence from the others.

As for the foreign exchange markets (Figure 3), in all the cases under study more than 50% of the computed values are negative, suggesting that during most of the sample period, these markets were importing volatility from the rest of markets, the GBP standing out as a significant net receiver (with 85.01% of negative values), followed by the CAD (with 76.44% of negative values). Nevertheless, it is interesting to note that for the cases of the USD, EUR, CAD, GBP and JPY at the beginning of the sample there are subperiods of net directional connectedness in volatility to the other markets.

Finally, and in relation to the evolution of the net directional connectedness between the stock markets and the foreign exchange markets in each country under study, in Figure 4 we can see that in all the cases more than 50% of the computed values are positive, indicating that during most of the sample period, the volatility in these stock markets crucially determined the volatility registered in their foreign exchange markets. It is noticeable the role of net volatility transmitters of the USA, Canada and the UK during the global financial crisis, as well as the intense peak around the collapse of Lehman Brothers.

3. Net pair-wise directional connectedness

So far, we have discussed the behavior of the total connectedness and total net directional connectedness measures for the fourteen stock and foreign exchange markets. However, we have also examined their net pair-wise directional connectedness during the financial turmoil periods experienced in the sample period. Figure 5 synthetically displays the main results for our dynamic analysis of the net pairwise directional connectedness among the 91 possible pairs formed from the 14 markets under study, focusing on cases where intensity was especially significant. That is, using of the Diebold and Yilmaz's (2014) graphical methodology, we provide a visualization of the complex network of innovation overflows among the 14 variables in our sample. The color of the arrows indicates the intensity of the connectedness among the variables: black, red and yellow links correspond, respectively, to the tenth, twentieth and thirtieth percentiles of all net pairwise directional connections between markets.

Specifically, Figure 5a displays stronger net pair-wise directional connectedness during the tequila crisis, suggesting that stock markets were the main triggers in the volatility connectedness relationships (representing the two thirds of the relationships). Conversely, during the ruble crisis and the dotcom crash (Figure 5c and 5d), the connectedness relationships account, respectively, for 63% and 65.22% of the total when foreign exchange markets are the triggers (especially in the thirtieth percentile, where only one relationship is detected departing from stock markets in both episodes). As for the Asian crisis (Figure 5b), our results suggest an almost equal distribution of the source of volatility, since 51.85% of the stronger connectedness relationships depart from exchange rate markets and 48.15% from stock markets. Remarkably, during the

global financial crisis (Figure 5e), only 44.4% of the most intensive connectedness linkages originated in the stock markets. Finally, both during the successive European sovereign crises (Figure 5f) and the Brexit referendum (Figure 5g), the foreign exchange markets are the triggers (representing two thirds of the detected relationships in the tenth and twentieth percentiles). Interestingly, in the latter case, the Eurostoxx 50 Index is found to be a significant net volatility receiver, confirming that Brexit-induced policy uncertainty also affects EU financial markets (see, e. g., Belke et al., 2018).

4. Concluding remarks.

Several financial as well as currency crises across emerging markets around the globe and the advent of floating exchange rate led the academicians along with practitioners to reconsider the nature of volatility spillovers, between stock and foreign exchange markets, that have seen large correlated movements resulting in market contagion. The recent global financial crisis of 2007–2009 has prompted renewed academic interest in financial market volatility. In this paper we investigated interdependence in volatility using a new method developed by Diebold and Yilmaz (2014). We focus on short-run volatility interaction effects within a system that comprises the stock and foreign exchange markets of the seven major world economies over the period between 6 July 1988 and 8 May 2018. We especially emphasized the analysis volatility transmission for the successive of financial crises registered during the sample period.

Our study may enhance the understanding of cross-market volatility dynamics in times of both turbulence and calm, and may help to assess the risk of crisis transmission.

The main findings of our research can be summarized as follows. In the first step, we found a system-wide value of 56.01% for the total connectedness between the fourteen markets under study for the full sample period. This level is much lower than that obtained by Diebold and Yilmaz (2012, 2014) for international financial markets and US financial institutions respectively. In the second step, we analyzed the dynamic nature of total net connectedness, obtaining evidence of spillovers showing large variation over time and supporting the literature documenting that volatility across markets increases during unstable periods such as the Asian crisis and the looming financial crisis in USA and Europe. In a third step, we examined the time-varying net

spillovers across markets, observing in all cases that the variables frequently switch between a net transmitting and a net receiving role. Finally, when analyzing net pairwise directional spillovers, our results suggest that throughout the tequila crisis, stock markets played a dominant role in the transmission of volatility, whereas during the ruble crisis, the dotcom crash, the global financial crisis, the European sovereign crises and the Brexit referendum, the foreign exchange markets were the main volatility triggers and during the Asian crisis there was an almost equal distribution of the source of volatility between stock markets and foreign exchange markets.

Our results may be of interest to policy-makers, who should take into consideration the spillover effects explained by the dynamic interdependences among the markets under study. Indeed, the connectedness measure can be used in a static or dynamic context, by showing the state of potential contagion at a certain point in time or a time dependent contagion index, allowing us to identify systemically relevant markets that can be a source of contagion and systemic risk, hence providing a macro-prudential toolbox for measuring the potential contagion using market data that can be adapted to the needs of policymakers by integrating other markets or extending it to real economy variables

A natural extension to the analysis presented in this paper would be to explore the main determinants of the detected net directional connectedness, with special emphasis in the economic and institutional factors. This is an item in our future research agenda.

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Table 1: Schematic connectedness table

	x_1	x_2	...	x_N	Connectedness from others
x_1	d_{11}^H	d_{12}^H	...	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	...	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H, j \neq 2$
.	.	.	.		
.	.	.	.		
.	.	.	.		
x_N	d_{N1}^H	d_{N2}^H	...	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H, j \neq N$
Connectedness to others	$\sum_{i=1}^N d_{i1}^H$ $i \neq 1$	$\sum_{i=1}^N d_{i2}^H$ $i \neq 2$	...	$\sum_{i=1}^N d_{iN}^H$ $i \neq N$	$\frac{1}{N} \sum_{i,j=1}^N d_{ij}^H$ $i \neq N$

Table 2: Full-sample connectedness

	SP500	EURO STOXX 50	AOI	SMI	TSX	FTSE100	NIKKEI 225	USD	EUR	AUD	CHF	CAD	GBP	JPY	Contribution FROM others
SP500	31.3067	8.7654	6.2531	5.8692	17.1472	11.0712	1.6027	1.1142	1.1079	5.6092	2.9784	4.7353	0.5621	1.8775	68.6933
EURO STOXX 50	11.1927	27.5094	4.7096	13.7481	8.2160	19.4856	0.7260	1.6003	1.9793	2.9485	1.2336	4.7597	0.4722	1.4193	72.4906
AOI	10.6388	5.7777	34.4193	5.0519	10.7068	7.3813	1.9577	4.0878	1.1905	6.2311	2.9328	6.3490	1.6741	1.6013	65.5807
SMI	7.1922	13.0592	4.1821	34.1290	6.0076	15.1580	1.4222	3.4940	1.8186	2.8459	4.0848	3.2723	0.4739	2.8601	65.8710
TSX	15.1784	7.3709	6.3413	5.2320	31.6280	10.2797	1.4824	3.2895	0.8776	5.4082	1.8834	5.3965	1.4040	4.2280	68.3720
FTSE100	10.0986	14.0365	4.4614	12.2957	9.4639	26.7853	1.0640	2.5879	1.4536	4.4861	2.8616	6.4006	0.8107	3.1941	73.2147
NIKKEI 225	6.4946	2.3573	2.7631	2.3551	3.5426	2.3611	64.8348	1.2086	0.4085	4.3076	1.4489	0.6945	0.5952	6.6281	35.1652
USD	1.6431	1.2746	2.5058	5.9222	5.7130	2.6251	2.3249	45.2831	4.5693	4.4805	7.4722	7.6556	2.6902	5.8405	54.7169
EUR	1.3437	3.2353	0.4679	4.0285	1.4374	2.9538	0.3149	4.6281	51.1602	1.1025	14.4997	3.5554	4.1108	7.1617	48.8398
AUD	5.1351	2.3581	4.1965	4.3177	8.4765	5.1857	2.2096	5.0915	1.4835	33.9603	3.4604	13.9400	2.4464	7.7387	66.0397
CHF	2.4117	0.6342	1.0261	2.1951	3.0831	0.6405	0.6183	5.5473	9.9210	0.9976	66.1515	1.6538	2.5263	2.5935	33.8485
CAD	3.2274	2.7013	2.5878	4.7996	6.7684	4.4364	0.4793	6.7316	1.8464	10.6256	3.3853	43.7872	3.5004	5.1234	56.2128
GBP	0.3578	0.5175	1.2319	0.5315	3.2563	0.2771	0.7102	3.0354	5.4065	3.1856	4.5101	5.7317	65.1820	6.0665	34.8180
JPY	1.5394	0.9569	0.3777	5.3268	5.6847	2.1318	5.0066	4.6790	3.4467	4.8296	1.2535	3.5520	1.4566	59.7587	40.2413
Contribution TO others	70.9478	69.6211	54.4258	67.7427	73.8896	75.8195	23.5019	50.9808	40.9709	62.6885	44.0135	60.7231	25.8493	48.5244	56.0075
Net contribution (TO –FROM) Others	2.2545	-2.8695	-11.1549	1.8717	5.5176	2.6049	-11.6633	-3.7361	-7.8688	-3.3512	10.1650	4.5103	-8.9687	8.2831	

Note: SP500, EURO STOXX 50, AOI, SMI, TSX, FTSE100, NIKKEI 225, USD, EUR, AUD, CHF, CAD, GBP and JPY stand for Standard & Poor's 500 composite index, Eurostoxx 50 Index, Australian All Ordinaries Index, Swiss Market Index, Toronto Stock Exchange index, Nikkei 225 index, Financial Times Stock Exchange 100 Index, US Dollar, Euro, Australian dollar, Swiss franc, Canadian dollar, British pound and Japanese yen effective exchange rates, respectively.

Figure 1: Rolling total connectedness

Notes:

The rolling estimation window width is 200 days, and the predictive horizon for the underlying variance decomposition is 10 days.

Vertical lines mark the start of major financial crisis: the tequila crisis (December 1994), the Asian crisis (July 1997), the ruble crisis (August 1998), the dotcom crash (March 2000), the global financial crisis (August 2007), the European sovereign crises (April 2009 and July 2012), the Russian financial crisis (June 2014) and the Brexit referendum (June 2016).

Figure 2: Net directional connectedness, stock markets

Figure 2: (continued)

Note: Net total directional connectedness for stock market i is “from i to others” less “from others to i ”.

Figure 3: Net directional connectedness, foreign exchange markets

Figure 3: (continued)

Note: Net total directional connectedness for foreign market i is “from i to others” less “from others to i ”.

Figure 4: Net directional connectedness: stock markets to foreign exchange market

Figure 4: (continued)

Note: Net total directional connectedness for stock market i to foreign market i

Figure 5: Net pair-wise directional connectedness before and after turmoil periods

Figure 5 (continued)

Figure 5 (continued)

Figure 5 (continued)

(g) Brexit

Note: Net pairwise directional connectedness during different subperiods. We show the most important directional connections among the 91 possible pairs formed from the 14 markets under study. Black, red and orange links (black, grey and light grey when viewed in grayscale) correspond to the tenth, twentieth and thirtieth percentiles of all net pair-wise directional connections.